Business Cycles and Stock Market Returns Predictability
Evidence from Continental Europe

Abed el Karim Salim Farroukh*

Masters in Finance Dissertation

Advisor: Júlio Fernando Seara Sequeira da Mota Lobão, Ph.D.

Co-Advisor: Natércia Silva Fortuna, Ph.D.

2016

* 201401008@fep.up.pt / karimfaroukh@gmail.com

Biographical Statement

Abed el Karim Farroukh was born in Lebanon in 1993. He completed his B.S. in Banking and Finance with a minor in Economics at the Lebanese American University before joining the Masters in Finance program at the Faculty of Economics and Management, University of Porto. As an Erasmus Mundus scholar, Abed was involved in several initiatives during his stay in Porto, among them the City Hall program “Classes Without Frontiers” in which he gave lectures to high school students. Additionally, he has served as the head of portfolio management team in FEP Finance club. Abed has developed a genuine interest for academia throughout the Masters in Finance program at U. Porto, and he is aiming to further his studies by joining the Ph.D. program in Business Administration with a Finance Specialization at the University of Washington.

Acknowledgements

My sincere gratitude to Professor Júlio Lobão for introducing me to the topic and for the readily provided guidance and supervision, Professor Natércia Fortuna for her help, my family for their prayers, Thomson Reuters for teaching me patience, my beloved companion for nurturing my stress management skills, librarians of the Faculty of Economics at U. Porto and Nova School of Business for their kindness, and finally Erasmus Mundus and the European Commission for giving me the chance to enroll in such a life changing experience.

Abstract

Business cycle patterns in common stock returns have been widely tested in the U.S. (e.g. Fama and French (1989), Korniotis and Kumar (2013)) and the UK (e.g. Priestley (1997), Velazquez and Smith (2013)). And despite the relevance of the topic, the literature seems to lack evidence from continental Europe. This study fills part of the gap through testing whether stock returns vary with business cycles in a predictable manner for a set of continental European countries. We collect a comprehensive set of data spanning from 1999Q4 till 2015Q4 and covering Portugal, Spain, Italy, France and Germany, then we regress residual returns from a market risk free rate of value-weighted country portfolios over lagged economic indicators that are likely to vary with the business cycle. The main findings of the study suggest that (i) country-level business cycle indicators are not robust predictors of stock returns and (ii) the Eurozone counterparts of these indicators incorporate more valuable information about future country-level stock returns. We present several economic justifications for our findings. First, stock market wealth accounts for a small percentage of household's net worth in continental Europe which makes it harder for short-run country-level economic fluctuations to propagate to the stock market. Second, the period covered by the study starts at the time of introducing the euro as a single currency and captures several economic crises; all of which are events that granted Eurozone indicators a significant predictive power of country stock returns because they contributed to: (i) financial and economic convergence of Eurozone economies (ii) increased comovements in Eurozone equity markets and (iii) higher regional equity bias to the detriment of home bias of European investors. Our findings have significant implications for investors using macroeconomic trading strategies to time the European equity markets.

Key words: stock returns predictability, business cycles, Eurozone
JEL Classification: G17, E30, E44

Resumo

O impacto das tendências dos ciclos económicos nas rendibilidades das ações tem sido um assunto amplamente testado para os mercados dos EUA (e. g., Fama e French (1989), Korniotis e Kumar (2013)) e do Reino Unido (e.g., Priestley (1997), Velazquez e Smith (2013)). Apesar da importância do tema, existe pouca investigação em amostras da Europa continental. Este estudo preenche essa lacuna ao testar se os retornos das ações variam de acordo com os ciclos de negócios de um modo previsível para um conjunto de países da Europa continental. Recolhemos um conjunto abrangente de dados que vão desde o 4º. trimestre de 1999 até ao 4º. trimestre de 2015, considerando os mercados de ações de Portugal, Espanha, Itália, França e Alemanha. Depois, foi efectuada uma regressão dos retornos residuais em função de indicadores económicos desfasados que previsivelmente devem variar com os ciclos económicos. Os principais resultados do estudo indicam que (i) os indicadores dos ciclos económicos nacionais não são úteis para fazer previsões sobre rendibilidades e que (ii) os indicadores homólogos da Zona Euro captam informações mais relevantes sobre retornos futuros ao nível do país. Apresentamos várias justificações económicas para estes resultados. Em primeiro lugar, a riqueza investida no mercado de ações é apenas uma pequena percentagem do valor líquido da riqueza das famílias da Europa continental, o que torna mais difícil que flutuações económicas de curto prazo ao nível do país se possam propagar no mercado de ações. Em segundo lugar, o período em que este estudo incide começa no momento da introdução do euro como moeda única e portanto abrange várias crises económicas nacionais; todos estes eventos levaram a que os indicadores da zona euro tivessem um poder de previsão mais significativo de retornos de ações ao nível de país, pois eles contribuíram: (i) para a convergência económica e financeira das economias da zona do euro, (ii) para o aumento de movimentos correlacionados nos mercados de ações da Zona Euro e (iii) para um maior enviesamento regional no investimento em ações em detrimento do tradicional enviesamento nacionais dos investidores europeus. Os nossos resultados têm implicações significativas para os investidores que usam estratégias de transação baseadas em indicadores macroeconómicos nos mercados de ações europeus.

Palavras-chave: previsibilidade dos retornos de ações, ciclos de negócios, Zona Euro
Classificação JEL: G17, E30, E44

Contents

Index of Tables

Index of Figures

1. Introduction

There is a longstanding interest in studying the interactions between business cycles and equity returns, and whether those interactions generate predictable return patterns that can be potentially exploited. The relevant literature widely covers the U.S. (e.g. Fama and French (1989), Korniotis and Kumar (2013)) and the UK (e.g. Priestley (1997), Velazquez and Smith (2013)) but misses continental Europe; we intend to fill part of this gap in the literature.

To the best of our knowledge, this is the first study examining whether stock returns vary with business cycles in a predictable manner for a set of continental European economies, namely Portugal, Spain, Italy, France and Germany. We rely on the paper by Korniotis and Kumar (2013) "State-Level Business Cycles and Local Return Predictability" as our benchmark study; the authors tested for state portfolio return predictability in the U.S. using state and aggregate U.S. level business cycle economic indicators. Conversely, we consider the Eurozone as the aggregate economy and we test for country-level return predictability using country and Eurozone business cycle variables.

First, we construct value weighted country portfolios including stocks of all companies headquartered in the country; we exclude companies with market capitalizations lower than 45000 USD because their return and market capitalization data is highly inconsistent. We use the residual return from a market risk free rate of the value-weighted portfolios as the dependent variable to ensure that our return series do not reflect variations in the European benchmark risk free rate. Our sample spans from 1999Q4 till 2015Q4 because some of the economic indicators are not available at a higher frequency for a longer time interval. The main explanatory variables are economic indicators that are likely to vary with the business cycle. Namely (i) growth rate of labor income defined as the log difference of labor income in the current quarter and the same quarter in the previous year, (ii) relative unemployment rate calculated as the ratio of the current level of unemployment to the moving average of unemployment rate in the past 16 quarters and (iii) yearly growth in housing prices defined as the log difference between housing prices index value in the current quarter and the same quarter in the previous year. We include the same indicators on a country and Eurozone level

because it allows us to test whether country stock returns capture trends in the aggregate Eurozone economy. In addition, we use the dividend yield of country portfolios as a control variable plus two Eurozone spreads; term spread calculated as the return difference between AAA-Eurozone 10-year government bond and AAA-Eurozone 1-year government bond and borrowing spread defined as the difference between Eurozone average corporate borrowing rate and Eurozone average government long-term bond yields.

The two main conclusions we draw from our return predictability regressions are (i) country level business cycle indicators are not robust predictors of country stock returns in Portugal, Spain, Italy, France and Germany, and (ii) the Eurozone counterparts of these indicators incorporate more valuable information about future country-level stock returns in the aforementioned countries. The results of our regressions are exactly the opposite of those obtained by Korniotis and Kumar (2013); the authors found that two of the three main state-level predictors were significant whereas all of their U.S. counterparts were not.

We present two main economic justifications for this contradiction. First, stock market wealth accounts for a lower percentage of household's net worth in continental European economies than in the U.S. which makes it harder for temporary country-level fluctuations in the business cycle to propagate to the stock market through household demand shocks. Second, the period covered by our study was marked by several economic developments that granted EU indicators more significant predictive power than their country-level counterparts. In particular, (i) the macroeconomic and financial convergence associated with introducing the euro as a single currency on the first of January 1999, (ii) the increase in regional equity bias to the detriment of home bias associated with the same event and (iii) the increased financial contagion phenomenon induced by the dotcom bubble, global financial crisis and to a lesser extent the European debt crisis.

The rest of the study proceeds as follows: section 2 reviews the literature, section 3 provides a comprehensive description of the data and methodology, section 4 shows the estimation output and presents the analysis, section 5 summarizes and concludes with suggestions for future research.

2. Literature Review

Do stock returns vary in a predictable manner? This question has been of longstanding interest to both academics and practitioners, and the evidence so far has been mixed. In the literature review, we start by relating predictability of asset returns to the Efficient Market Hypothesis, then we discuss various approaches to the predictability debate. The topics we cover, in the order they appear in the review, are (i) business cycle patterns in common stock returns (ii) asset pricing models and return predictability (iii) the predictive power of monetary policy variables (iv) inflation and asset returns (v) the predictive power of popular fundamental ratios (vi) the forecasting ability of other ratios (vii) other approaches to the predictability debate (viii) evidence against the predictability literature and (ix) defense of predictability. Each paragraph signals a new topic in the predictability literature and the final paragraphs states concluding remarks, we respect the chronological order of studies within each paragraph in most of the cases.

Much of the more recent predictability literature was motivated by the Efficient Market Hypothesis; it was claimed that evidence on return predictability would be inconsistent with the efficiency paradigm. However, nowadays, predictability of time varying-expected returns and market efficiency can coexist, and the attention is more directed towards how much predictability is compatible with efficient markets (Lanne, 2002). Both behaviorists and efficiency proponents agree that expected returns are predictable; but they disagree whether this predictability is caused by rational or irrational variations in risk. This was illustrated by Eugene Fama in his Nobel Prize lecture:

"Efficient market types (like me) judge that predictable variation in expected returns on stocks and bonds is rational, the result of variation in risk or willingness to bear risk. In contrast, behaviorists argue that much of the predictability is due to irrational swings of prices away from fundamental values." (Fama, 2013, p. 9)

Business cycle patterns in common stock returns have been widely tested. Fama and French (1989) conjectured that expected returns are higher (lower) when economic conditions are weak (strong). They used the default spread (yield difference between the market portfolio

of corporate bonds and Aaa bonds) and the dividend yield ratio to track long term business conditions, and the term spread (difference between Aaa yield and 1-month T-bill rate) to track the shorter-term business cycles. The three variables were able to predict stock and bond returns suggesting that variations in expected returns are related to long-and-short-term variations in the business cycle. Priestley (1997) tested for cyclicality in UK stock returns and found that return seasonality is caused by the high risk associated with holding stocks in some periods of the year, namely January and December, because those periods are important in the yearly business cycle and can significantly indicate current and following levels of economic activity. The author also found evidence for April effect and suggested that it might be due to the timing of the UK tax year end and UK annual Government Budget, both of which are events that may have implications on future levels of economic activity. Chordia and Shivakumar (2002) used all NYSE-AMEX stocks to show that payoffs to momentum strategies can be explained by a parsimonious set of lagged macroeconomic indicators that vary with the business cycle. Velazquez and Smith (2013) examined business cycles and equity returns using a long period of UK data and confirmed the counter-cyclicality of equity returns; returns tend to be higher following recession quarters rather than expansion ones.

In addition to the direct business cycle analysis, many equilibrium and asset pricing models aimed to predict and explain the pro-cyclical variation in stock returns. Balvers et al. (1990) developed an equilibrium model relating asset returns to fluctuations in output; they argued that output fluctuations lead investors to smooth consumption by adjusting their required rate of return on financial assets. The authors adopted assumptions from real business cycle models to show that output is auto-correlated, then suggested that output forecasts can predict stock returns in the U.S., UK, Canada and Japan. Cochrane (1991) developed a production-based asset pricing model that was able to explain two links between returns and the business cycle: (i) several variables forecast stock returns and (ii) many of those variables, and stock returns, forecast economic activity measures. Campbell and Cochrane (1999) constructed a consumption based model that uses mean reversion in returns and the dividend-price ratio to generate long horizon forecasts of excess stock returns. Their model was able to capture the main business cycle swings in stock prices over the past hundred years when fed with actual consumption data. Similarly, Yogo (2006) developed a consumption-based model and

concluded that returns on value and small stocks show higher pro-cyclicality than those on growth and big stocks, equity premium is highly countercyclical and returns tend to be unexpectedly high (low) during booms (recessions).

A significant part of the literature studied the predictive role of monetary policy. Patelis (1997) proposed a new set of monetary policy variables that can significantly predict stock returns, namely the federal funds rate, interest rate spreads, the quantity of non-borrowed reserves and the portion of non-borrowed reserve growth orthogonal to total reserve growth. The author used nested regressions to show that the predictive power of monetary variables is distinct from that of popular financial variables. Thorbecke (1997) utilized a similar set of monetary indicators and suggested that expansionary monetary policy increases ex-post stock returns. The aforementioned findings, among others, were subject to a lot of scrutiny. Durham (2003) argued that the relationship between monetary policy and stock returns is less vigorous than indicated by previous studies. Through analyzing a comprehensive set of data for 16 countries, Durham (2003) showed that the statistical significance vanishes when using excess return as the dependent variable, dividing the sample period into smaller sub-periods, or utilizing panel regressions.

In regards to inflation; Nelson (1976), Bodie (1976), Jaffe and Mandelker (1976) as well as Fama and Schwert (1977) documented a negative relationship between stock returns and both expected and unexpected components of inflation (Fama, 1981). This contradicts Fisher's hypothesis that on average investors will be fully rewarded for any deterioration in purchasing power (Fisher, 1930). Fama (1981) investigated those findings and found that much of the negative evidence is due to proxy effects. He conjectured that forecasts of more relevant real variables determine stock returns, and the negative relation between return and inflation is caused by negative inflation-real activity relations.

In addition to the work targeting empirical linkages between the macro-economy and stock returns, the predictive power of fundamental variables has been widely tested. Campbell and Shiller (1988) showed that the ratio of a long moving average of real earnings to the current stock price can powerfully predict long term stock returns. Fama and French (1988) found that the dividend yield explains less than 5% of variances of monthly or quarterly returns but

can explain more than 25% of return variances when considering two to four year horizons. Evidence of the forecasting and explanatory abilities of fundamental variables was also documented outside of the U.S.; Chan et al. (1991) found a significant relationship between expected returns in Japan and earnings yield, cash flow yield, book to market ratio and size. Similarly, Mukherji et al. (1997) found a positive relationship between annual stock returns in Korea during the 1982-1993 period and book to market, sales to price and dividends to earnings ratios.

The forecasting ability of ratios such as the consumption-aggregate wealth ratio (*cay*) and housing collateral ratio (*hy*) was also tested. Lettau and Ludvigson (2001) argued that the cay residual demonstrates better forecasting abilities than the dividend yield and dividend payout ratios on both the short and intermediate terms. Sousa (2010) used UK and U.S. data to show that disintegrating the wealth from cay into housing and financial wealth improves forecasts of stock returns. In contrast, Hamburg et al. (2005) tested *cay*'s predictive power using German data and found that it predicts income changes rather than stock market fluctuations. On a different note, Lustig and van Nieuwerburgh (2005) used the *hy* ratio defined as the log ratio of housing equity to labor income to show that changes in house prices can explain fluctuations in asset returns. They reasoned that a decline in house prices decreases the collateral value of houses which adversely affects risk sharing, this leads to an increase in the conditional market price of risk caused by an increase in household's exposure to idiosyncratic risk. Thus, a decrease in hy predicts higher market returns.

Several other perspectives were used to approach the predictability debate. Huang and Stoll (1994) studied the predictive power of market microstructure variables and found that expected transaction return is negatively related to the deviation between transaction prices and quote midpoint, while expected quote return is positively related to the same variable. Eleswarapu and Reinganum (2004) found evidence suggesting that stock market returns are forecastable by returns on glamour stocks in the prior 3-year period; they showed that the predictive power of glamour stock returns remains robust after introducing variables such as the dividend yield, cay, default and term premiums as control variables. In addition, Doukas et al. (2006) documented a positive relationship between divergence of investors' opinions

about the value of a stock and its future return, which contradicts the overvaluation hypothesis proposed by Miller (1977).

Volatility, sentiments and demographics were also used to explain and forecast returns. French et al. (1987) documented a positive relationship between the expected risk premium on common stocks and the predictable volatility of stock returns. Neal and Whealtley (1998) suggested that sentiment variables such as net redemptions and fund discounts are able to predict the size premium. Edmans et al. (2007) used international soccer results as a primary mood variable and found that losses in the elimination stage of the World Cup result in -49 bp abnormal stock return in the next day. On a different note, Goyal (2004) analyzed U.S. data to show that an increase in the middle-age population leads to higher short-run returns and lower long-run ones, whereas an increase in the old-age population leads to parallel but opposite effects.

Evidence of return predictability was subject to a lot of scrutiny. Stambaugh (1986) as well as Mankiw and Shapiro (1986) argued that using pre-determined variables as explanatory factors will lead to over-rejecting the non-predictability hypothesis. Nelson and Kim (1993) as well as Lanne (2002) highlighted problems that often lead to spurious results when employing standard methods to test for return predictability. First, all typical predictive variables are substantially persistent and their univariate representation has a considerable autoregressive root. Second, overlapping data in long-horizon regressions causes serial correlations in the error term. Lanne (2002) showed that the standard t-test over-rejects and suggested a stationary test to argue that no persistent variable, including the dividend yield, can predict U.S. stock returns in the 1928-1996 period. Campbell and Yogo (2006) confirmed persistence as a serious issue for both dividend yield and smoothed earnings-price; they designed a pre-test to show that t-test inferences are invalid for both ratios. The authors found evidence for predictability using interest rate variables that survived their pre-test, and concluded that predictability is harder to find compared to what suggested by previous studies.

Likewise, non-standard econometric methods demonstrated evidence against the predictive power of several popular forecasting ratios. Goetzmann and Jorion (1993) employed the

bootstrap methodology and found that dividend yields cannot predict U.S. stock returns between the years 1927 and 1990. Wolf (2000) used subsampling, which is superior to both VAR and bootstrap, and found no evidence in favor of predictability of U.S. stock returns by the dividend yield. On a similar note, Cooper et al. (2005) used a recursive out of sample method to test whether real time investors could have forecasted returns over the 1974-1997 period using size, book to market and momentum effects. They found that the market was hard to beat and showed a remarkable difference between ex-post and ex-ante predictability, which raises doubts about plenty of the predictability evidence. Moreover, Hjalmarsson (2010) tested for predictability in 24 developed and 16 emerging economies using an alternative robust estimator to the standard fixed effects model. He found no evidence supporting the dividend yield and earning price ratios as return predictors; however, both term spread and short interest rate showed robust forecasting abilities in developed markets.

Evidence against the predictability literature sparked several comeback attempts by the latter's proponents. Boudoukh et al. (2007) showed that mismeasurement is more responsible for demising the dividend yield as a return predictor than factors such as spurious correlations and learning. The legislation of the rule 10b-18 in 1982 sparked a surge in repurchase activity, which affected the way firms distribute earnings to shareholders. Thus, the total payout ratio (dividends plus repurchases) is a better return predictor than the dividend yield. The study showed that the dividend yield exhibits significant dynamic changes around the time of the aforementioned SEC legislation, and its predictive power declines subsequently when post 1984 data are incorporated in the analysis. On the contrary, payout yields exhibit no significant changes, and their forecasting ability stays robust across different time periods. Cochrane (2008) argued that if returns are not predictable, then dividend growth must be predictable to generate the observed fluctuation in the dividend yield ratio. However, he found no evidence that higher price-dividend ratios are correlated with higher dividend growth afterwards. Lettau and Nieuwerburgh (2008) suggested a procedure to extract the stationary component of popular forecasting price ratios. The adjusted ratios were significant and stable in predicting future returns in sample and functioned better than the unadjusted ones out of sample. Among the latest evidence presented in favor of return predictability is our benchmark paper by Korniotis and Kumar (2013). The authors conjectured that changes

in local macroeconomic conditions can induce shifts in risk aversion and risk sharing levels, which, in presence of high local ownership, produces predictable patterns in stock returns through negative demand shocks by local investors. The predictability evidence presented in the paper is robust to problems of persistence and endogeneity, and is preserved when employing bootstrap or recursive methods.

The scientific knowledge in the predictability field has progressed from Fama and French (1988): "There is much evidence that stock returns are predictable." To authors using titles as "Spurious Regressions in Financial Economics" (Ferson et al. 2003) and "Testing the Predictability of Stock Returns" (Lanne, 2002); which made it necessary for the literature to attempt "Reconciling the Return Predictability Evidence" (Lettau and Nieuwerburgh, 2008). The predictability debate is far from over. Our study provides evidence from Europe; we use the most comprehensive set of data covering five major economies in Continental Europe to analyze the interactions between business cycle variables and stock returns.

3. Data and Methodology

This chapter presents a comprehensive description of the data collection process and choice of variables. First we justify our choice of countries included in the study, then we show how we construct country portfolios and derive the residual return series. After that we reason our choice of macroeconomic indicators and finally we present the table of descriptive statistics and describe the methodological aspects of the study.

3.1. Choice of Countries

Korniotis and Kumar (2013) conjectured that short-term economic fluctuations can influence stock returns through demand shocks by local investors. Hence, investigating the interactions between country-level business cycles and stock returns becomes more reasonable when local stocks are owned by investors residing in the same country. Therefore, our sample of European countries takes into consideration the levels of local equity ownership as well as the availability of macroeconomic data on a quarterly frequency for a sufficient time span. Table 1 shows equity and bond home bias levels for EU-14 countries plus the UK and U.S.

Table 1: Equity and bond home bias levels, 1997-2012

	Equity home bias					Bond home bias				
	1997	2004	2012	Δ 97–04	Δ 04–12	1997	2004	2012	Δ 97–04	Δ 04–12
Austria	0.81	0.67	0.65	-0.14	-0.02	0.81	0.66	0.75	-0.14	0.08
Belgium	0.86	0.72	0.74	-0.14	0.02	0.82	0.58	0.67	-0.24	0.09
Denmark	0.83	0.73	0.63	-0.10	-0.11	0.91	0.87	0.87	-0.04	0.00
Finland	0.96	0.75	0.61	-0.21	-0.14	0.93	0.60	0.61	-0.33	0.01
France	0.90	0.79	0.79	-0.11	0.01	0.87	0.69	0.76	-0.18	0.07
Germany	1.00	0.77	0.80	-0.23	0.03	1.00	0.80	0.73	-0.20	-0.07
Greece	1.00	0.97	0.98	-0.03	0.01	1.00	0.83	0.86	-0.17	0.03
Italy	0.89	0.84	0.78	-0.04	-0.07	0.93	0.84	0.91	-0.10	0.07
Netherlands	0.77	0.44	0.49	-0.33	0.05	0.75	0.61	0.70	-0.14	0.09
Poland	1.00	0.99	0.99	-0.01	0.00	n/a	0.99	1.00	n/a	0.00
Portugal	0.94	0.86	0.80	-0.09	-0.06	0.87	0.67	0.84	-0.20	0.17
Spain	0.95	0.93	0.94	-0.02	0.02	0.95	0.68	0.93	-0.26	0.24
Sweden	0.87	0.73	0.70	-0.14	-0.03	n/a	0.83	0.88	n/a	0.05
UK	0.84	0.80	0.76	-0.04	-0.04	0.73	0.78	0.82	0.05	0.03
US	0.84	0.82	0.75	-0.02	-0.06	0.95	0.96	0.96	0.01	0.00
EU-14	0.85	0.77	0.75	-0.08	-0.03	0.84	0.73	0.82	-0.10	0.08
Euro area	0.86	0.76	0.74	-0.10	-0.02	0.87	0.70	0.81	-0.17	0.11
Non-euro area	0.84	0.79	0.75	-0.06	-0.04	0.76	0.80	0.83	0.04	0.03

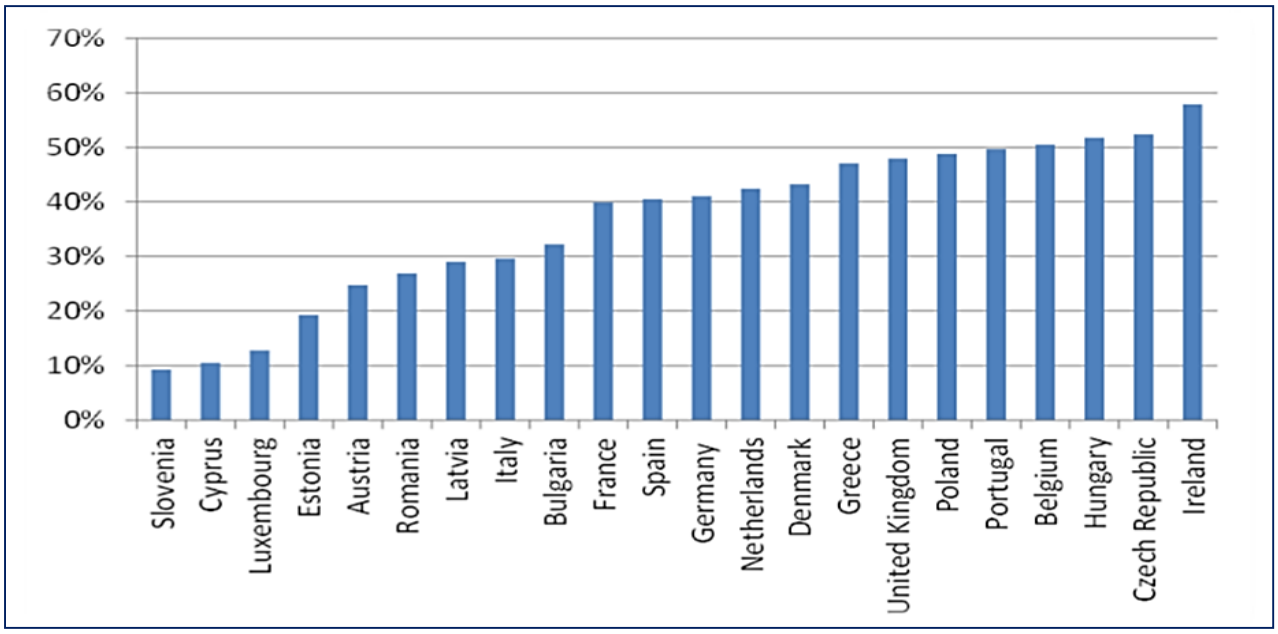
Source. Schoenmaker and Soeter (2014).
Note. Table 1 presents a country breakdown of equity and bond home bias levels for all EU-14 countries as well as the U.S. and UK. Home bias levels vary from zero to one and assume a value of zero when investors show no preference for local equity.

All the listed countries maintain extremely high levels of home bias in the 1997-2012 period. However, this is not enough to prove high local ownership because home bias measures the extent to which a country over-invests in its own equity, or in other words, the extent to which a country invests in its own equity beyond the optimal investment level from a diversification point of view (Schoenmaker and Soeter, 2014). Therefore, local ownership can be low despite high home bias levels; this can be the case in any country where local investors over-invest in local equity but the combined dollar value of their investments in local stocks is low relative to that of foreign investors. In this case home bias is high because local investors do not benefit from cross-country diversification, but local ownership is low because the portion of local market capitalization owned by local investors is low compared to that owned by foreign investors.

We followed the sources used by the authors and tried to calculate the ratio of foreign to total portfolio investment assets (equity and investment fund shares) for European countries using the IMF Consolidated Portfolio Investment Survey (CPIS) data. However, for many countries the ratio was greater than 1 and the data was not entirely consistent. Balta and Delgado (2009) mentioned that CPIS data are inaccurate, underreported and fail to track the end investors.

Therefore, we had to find an alternative source. A report titled “Who Owns the European Economy? Evolution of The Ownership of EU-Listed Companies Between 1970 and 2012” by Davidoff et al. (2013) used rigorous data sets to construct Figure 1.

Figure 1: Share of foreign investors in total market capitalization, 2011



Source. Davidoff et al. (2013).
Note. Figure 1 shows the percentage of domestic market capitalization owned by foreign investor for a set of European countries.

A foreign investor, as identified by the report, is an equity owner who does not reside in the same country in which the company is based. Thus, by subtracting the values in the graph from 100% we obtain the levels of local equity ownership.

Considering the location of our Master's program; we are curious conduct our study in Portugal and the neighboring economies. Therefore, we perform the analysis on Portugal, Spain, Italy, France and Germany; all of which are countries with levels of local equity ownership greater than 50%. Since the report showed an increasing trend in the share of foreign investors starting in the beginning of the 1980s except for a slight decrease during the financial crisis; we can conjecture that levels of local equity ownership were generally higher before 2011. Our study covers the interval 1999Q4-2015Q4, therefore, local equity ownership is evidently very high for the vast majority of the studied period.

3.2. Constructing Country Portfolios

We investigate the relation between country-level macroeconomic indicators and stock returns by using the return series of value-weighted country portfolios. We use quarterly data for the period 1999Q4-2015Q4 because some of our macroeconomic indicators are not available on a monthly basis and for a longer time span.

Korniotis and Kumar (2013) followed the convention in the local bias literature (e.g., Pirinsky and Wang (2006), Hong et al. (2008)) to proxy for firm location using corporate headquarters location. We follow the same convention in our study.

Data for corporate headquarters location are obtained from Thomson Reuters Eikon using the "Equity Screener" function. We screen all active public companies with a minimum market capitalization of 45000 USD by filtering for the country of headquarters. This results in 57 companies headquartered in Portugal, 220 in Spain, 323 in Italy, 1128 in France and 994 in Germany. We use the 45000 USD market capitalization criterion because it filters out much of the inconsistent return and market capitalization data while excluding only a negligible number of the consistent ones.

Thomson Reuters Eikon's function "Portfolios and Lists" allows creating value weighted portfolios, however the function provides only two years of quarterly historical return data which is not enough to conduct our study. Therefore, we had to construct the portfolios manually using historical return and market capitalization data for all retrieved stocks.

We use the filtered results from the screener function to obtain quarterly returns[1] and market capitalization data for all of the companies. Considering the size of the portfolios and the large amount of data, some of the retrieved values showed inconsistencies and suffered errors that could be avoided through retrieving data for each individual company on its own (this was not the case for the filtered out small cap stocks because their data remained inconsistent even when we tried to retrieve them individually). Therefore, in order to avoid any error that

[1] Quarterly return, as defined by Thomson Reuters, incorporate price changes and any relevant dividends paid within the quarter.

might bias our results, we went over the data and re-retrieved inconsistent values for each company individually. Data for some of the stocks were still inconsistent even when retrieved alone; we exclude these stocks from our analysis and we end up with portfolios of: 50 companies in Portugal, 189 in Spain, 309 in Italy, 925 in France and 873 in Germany[2].

The final portfolios represent more than 96% of the total market capitalization of all filtered companies in each of the aforementioned countries. Therefore, we conjecture that the return series we use in this study are representative of the country-level return series.

Our portfolios are value weighted and adjusted to changes in market capitalizations on a quarterly basis. Thus, we construct our return series using lagged values of the relative market capitalization following equation (3.2.1):

$$Y_{i,t} = \sum \frac{Mkt\ Cap_{c,i,t-1}}{Total\ Mkt\ Cap_{i,t-1}} * Y_{c,t} \qquad (3.2.1)$$

where $Y_{i,t}$ is the portfolio return of country *i* at quarter *t*. On the right side of the equation, the numerator is the market capitalization at quarter *t-1* of company *c* headquartered in country *i*, the denominator is the sum at quarter *t-1*of market capitalizations of all companies headquartered in country *i*. Therefore, the fraction gives the relative weight of company *c* stocks in the portfolio, invested at quarter *t-1*. Thus, multiplying the fraction by the return of the stock at quarter *t* gives the return earned by the portfolio from that specific stock. Performing the same procedure for all stocks in the portfolio then adding the returns will result in the country portfolio return series.

To ensure that our return series capture the country-specific component of return and do not reflect variations in the European benchmark risk free rate, we estimate the residual from a market risk free rate model in which the risk free rate of return is the only dependent variable. First, we correct the nominal returns of the five portfolios for the inflation level in each country. We retrieve quarterly inflation rates for the five countries from the IFO Institute World Economic Survey data available via DataStream, then we divide quarterly returns by

[2] Appendix A shows tables with identifiers of all excluded stocks in addition to detailed calculations on the portfolios' representativeness of country-level market capitalization.

1+inflation rate to obtain real returns. We use the redemption yield (yield to maturity) of 3-month German T-bills to proxy for the risk free rate of return. Annualized data of the redemption yield are retrieved from an index by Thomson Reuters also available on DataStream, we calculate the quarterly yields as follows:

$$quarterly\ yield = \left[(1 + annual\ yield)\text{^}\left(\frac{1}{4}\right)\right] - 1 \tag{3.2.2}$$

3.3. Economic Indicators

In this section we justify our choice of economic indicators. Whenever possible, we use the same indicators as Korniotis and Kumar (2013), however, due to fundamental differences in the geographical coverage of the two studies, our set of utilized indicators is not an exact copy of the benchmark study. Nevertheless, the economic intuition is the same.

Korniotis and Kumar (2013) tested for business cycle swings of stock returns on a state level in the U.S. They constructed state-level portfolios and considered each state a separate economy with its own economic indicators. In addition, the authors used U.S. economic indicators to ensure that state portfolios do not reflect trends in the aggregate U.S. economy. Following the same intuition, we utilize country-level economic indicators as well as Eurozone indicators to test if country-level returns reflect Eurozone trends.

We consider three main country-level return predictors that are likely to move with the business cycle:

i. Growth rate of country level labor income, this measure is defined as the log difference between country-level labor income in a given quarter and country-level labor income in the same quarter of the previous year. Based on Jagannathan and Wang (1996) as well as Campbell (1996); Korniotis and Kumar (2013) use this measure to proxy for return to human capital.

   We obtain data on wages and salaries from Eurostat via DataStream, this indicator as well as the rest of the economic indicators we use are not seasonally adjusted.

ii. Relative unemployment rate defined as the ratio of the current level of unemployment to the average unemployment rate in the prior 16 quarters. Korniotis and Kumar (2013) used this measure as a recession indicator for the state economy, we use it as a recession indicator on a country level. The average unemployment rate in the prior 16 quarters proxies the natural rate of unemployment, (un)favorable deviations of the current levels of unemployment from the natural rate signal (bad)good news for the economy.

We obtain quarterly unadjusted unemployment rates from DataStream. For Portugal, Spain, Italy and Germany the data are sourced from National Institutes for Statistics. Whereas for France, we use the data provided by OECD Main Economic Indicators because all unemployment rates provided by INSEE (the French National Institute for Statistics and Economic Studies) are seasonally adjusted.

iii. Our third economic indicator captures house-price developments; we use the house price indices provided by Oxford Economics and available on DataStream to calculate the yearly log difference in house prices within each of the studied countries. This measure is defined as the log difference between the index value in a given quarter and its value in the same quarter of the previous year. For Portugal, Italy France and Germany the price indices provide complete historical data for the full time span of our study, whereas for Spain, the index value from 2014Q2 onwards is based on forecasts by Oxford Economics. According to Lustig and van Nieuwerburgh (2005), a decrease in house prices decreases the collateral value of houses which adversely affects risk sharing abilities. This increases investors' exposure to idiosyncratic risk and raises the conditional market price of risk. Lustig and van Nieuwerburgh (2005) constructed a housing collateral ratio (*hy),* then showed that a lower U.S. *hy* forecasts higher market returns. Korniotis and Kumar (2013) used *hy* to proxy for investors' ability to borrow against housing collateral and to effectively smooth consumption against future income shocks. We use the yearly log difference in a house price index to capture variations in the housing collateral ratio and to proxy for changes in the collateral value of houses.

In addition to the three main predictors, we include the dividend yields of country portfolios as control variables. We use the ISIN codes of our stocks to retrieve quarterly dividend yield data from DataStream, then we compute the quarterly value-weighted dividend yields for our

country portfolios by replacing Y with DY (dividend yield) in equation (3.2.1). Our quarterly dividend yield series is defined as the log of 1+DY of country portfolios. DataStream yields exclude special or once-off dividends and are computed based on the anticipated annual dividend per share as a percentage of the current share price.

To ensure that state predictors do not solely capture the impact of the aggregate U.S. economic shocks, Korniotis and Kumar (2013) added several U.S. level macroeconomic indicators to their regression specification. The authors used the same state-level measures using U.S. data in addition to the U.S. cay (consumption-wealth) ratio and three return spreads (paper-bill, term and default spreads).

Our study considers the Eurozone as the aggregate economy, therefore we incorporate Eurozone business cycle indicators in the analysis to test whether country-level stock returns are predictable by variations in the aggregate Eurozone business cycle. Accordingly, we use the same three main country-level indicators on a Eurozone level in addition to the following return spreads:

i- Term spread: return difference between AAA-Eurozone 10-year government bond and AAA-Eurozone 1-year government bond. Data is obtained directly from Eurostat.

ii- Corporate borrowing spread: difference between Eurozone average corporate borrowing rate and Eurozone average government long-term bond yields. The average corporate borrowing rate data are provided by Oxford Economics, whereas the Eurozone average government long-term bond yield data are provided by Eurostat; both series are retrieved via DataStream.

We obtain Eurozone and country-level data from the same sources. Eurozone unemployment rates are retrieved from OECD Main Economic Indicators via DataStream and the Eurozone house price index by Oxford Economics provides complete historical data for the whole timespan of our study.

All of the economic indicators are not seasonally adjusted and all our return predictors are corrected for the respective quarterly inflation rate.

3.4. Descriptive Statistics

Table 2 presents the descriptive statistics for each of the variables we use in the analysis. The table is generated via EViews and reproduced to fit in the document.

Table 2: Descriptive statistics

Variable	Symbol	Mean	Median	Maximum	Minimum	Std. Dev.	Obs.
Residual Return	RR	1.23E-11	0.278764	44.83195	-32.3345	10.31554	325
Labor Income Growth	INC	0.011788	0.013579	0.040094	-0.04707	0.013322	345
Rel. Unemployment	RU	0.994476	0.966133	1.826756	0.58887	0.212342	345
Housing Prices Growth	YHG	0.01221	0.009705	0.070376	-0.04387	0.024684	345
log (1+ div yield)	DIV	0.013464	0.012693	0.034834	0.004541	0.005211	340
EU Labor Income Growth	INCEU	0.013132	0.012488	0.026263	-0.00052	0.007053	345
EU Rel. Unemployment	RUEU	0.984222	0.976891	1.268463	0.792482	0.123872	345
EU Housing Prices Growth	YHGEU	0.012417	0.016964	0.030884	-0.01895	0.014088	345
Term Spread	TERM	1.464279	1.554572	2.986248	0.126582	0.770277	340
Borrowing Spread	BORROW	0.308978	0.252797	1.658723	-0.71705	0.525301	340

Note. Table 2 reports the descriptive statistics for country portfolio returns and return predictors. The sample spans from 1999Q4 till 2015Q4. The return series we use is the residual return from a market risk free rate of a value weighted portfolio that includes all companies headquartered in the country, we exclude companies with market capitalization less than 45000 USD The benchmark risk free rate in the analysis is the yield to maturity of 3-month German T-bills obtained from DataStream. The returns as well as the return predictors are corrected for the relevant inflation rate obtained from the IFO Institute World Economic Survey via DataStream. The main return predictors are (i) labor income growth (log difference of labor income in current quarter and the same quarter in the previous year) obtained from Eurostat via DataStream, (ii) relative unemployment rate (ratio of current unemployment rate to moving average of unemployment in the past 16 quarters) obtained from National Institutes of Statistics and OECD Main Economic Indicators via DataStream, and (iii) growth in house prices (log difference of house price index in current quarter and the same quarter in the previous year) obtained from Oxford Economic also via DataStream. The main return predictors are not seasonally adjusted and are employed on both country and Eurozone levels. In addition, we use log (1+dividend yield) of country portfolios as a control variable as well as two Eurozone spreads; term spread (return difference between AAA-Eurozone 10-year government bond and AAA-Eurozone 1-year government bond) from Eurostat and borrowing spread (difference between Eurozone average corporate borrowing rate and Eurozone average government long-term bond yields) from Oxford Economic and Eurostat via DataStream. The residual return from a market risk free rate as well as both the term and borrowing spreads show high standard deviations because our sample covers periods of turmoil and crises. The values of Eurozone measures are smoother and more clustered around their means than the analogous country-level measures, this is reflected in a relatively lower standard deviation.

3.5. Methodology

Following the theoretical motivation of Korniotis and Kumar (2013), we consider a representative investor who owns a significant proportion of all public companies headquartered in her country of residence. Given that, the levels of risk aversion of the representative investor as well as her attempts to smooth consumption can influence stock returns. During business cycle recessions signaled by unemployment news or labor income shocks, the representative investor becomes more risk averse, thus she reduces her exposure to risky assets or requires a higher premium to invest in local stocks which depresses prices and generates predictable patterns in stock returns. Similarly, when the representative investor's borrowing capacity against housing collateral deteriorates due to a decrease in house prices, her ability to share risk becomes higher which increases her exposure to idiosyncratic risk and increases the market price of risk. In this case stocks must offer higher future returns to remain attractive. As such, short-term economic fluctuations induced by the business cycle should be able to generate predictable patterns in stock returns.

We test whether stock returns vary with the business cycle in a predictable manner in Portugal, Spain, Italy, France and Germany. We use the residual return from a market risk free rate as the dependent variable to ensure that our return series do not reflect variations in the European benchmark risk free rate. Our main explanatory variables are economic indicators that are likely to vary with the business cycle, namely labor income growth, relative unemployment rate and growth in a house price index. We include the same indicators on a country and Eurozone levels because it allows us to test whether country stock returns capture trends in the aggregate Eurozone business cycle. In addition to the three main predictors, we include the dividend yield of country portfolios as a control variable plus two Eurozone spreads: term spread and corporate borrowing spread. Therefore, the basic empirical model looks as follows:

$$\begin{aligned} rr_{i,t} = c &+ B_1 inc_{i,t-2} + B_2 ru_{i,t-2} + B_3 yhg_{i,t-2} + B_4 div_{i,t-1} \\ &+ B_5 inc_{EU,t-2} + B_6 ru_{EU,t-2} + B_7 yhg_{EU,t-2} \\ &+ B_8 term_{EU,t-1} + B_9 borrow_{EU,t-1} + \varepsilon_{i,t}, i = 1, \dots, 5, \\ &t = 1, \dots, 65 \end{aligned} \qquad (3.5.1)$$

where *i* refers to the country, *t* to the quarterly time period and *EU* to the Eurozone. $rr_{i,t}$ is the residual return from a market risk free rate of country *i* at quarter *t*. On the right hand side of the equation, *c* is the constant term. *inc, ru and yhg* are the macroeconomic indicators representing income growth, relative unemployment rate and yearly growth in a house price index respectively. *div* refers to log (1+dividend yield) of country portfolios, *term* and *borrow* refer to the term spread and borrowing spread respectively and $\varepsilon_{i,t}$ is the error term. We use *div, term* and *borrow* with a lag of one quarter, whereas the macroeconomic indicators are employed from quarter *t-2* because they are usually reported with a lag of two quarters.

Our sample covers the 1999Q4-2015Q4 interval, a major event that took place during that period and might have caused a structural change to the model was the financial crisis. Therefore, in order to have deeper insights on the behavior of the model in that specific period and to test for the significance of the change brought by the crisis, we introduced a dummy variable denoted by *crisis.* We consider the period of the financial crisis as the duration between two business cycle peaks identified by the Centre for Economic Policy Research[3] (CEPR, 2016), hence, *crisis* assumes a value of 1 from 2008Q1 until 2011Q3 and zero otherwise. The model with the dummy variable becomes:

$$\begin{aligned} rr_{i,t} = c &+ B_1 inc_{i,t-2} + B_2 ru_{i,t-2} + B_3 yhg_{i,t-2} + B_4 div_{i,t-1} \\ &+ B_5 inc_{EU,t-2} + B_6 ru_{EU,t-2} + B_7 yhg_{EU,t-2} \\ &+ B_8 term_{EU,t-1} + B_9 borrow_{EU,t-1} + B_{10} crisis \\ &+ B_{11} inc_{i,t-2} * crisis + B_{12} ru_{i,t-2} * crisis + B_{13} yhg_{i,t-2} \\ &* crisis + B_{14} div_{i,t-1} * crisis + B_{15} inc_{EU,t-2} * crisis \\ &+ B_{16} ru_{EU,t-2} * crisis + B_{17} yhg_{EU,t-2} * crisis \\ &+ B_{18} term_{EU,t-1} * crisis + B_{19} borrow_{EU,t-1} * crisis \\ &+ \varepsilon_{i,t}, i = 1, \dots, 5, t = 1, \dots, 65 \end{aligned} \tag{3.5.2}$$

By multiplying the dummy variable with the rest of variables we are able to estimate the coefficients for all of the predictors in the financial crisis and compare them with the full

[3] http://cepr.org/content/euro-area-business-cycle-dating-committee.

sample estimates. We also include the variable *crisis* on its own to test the significance of the structural change sparked by the crisis.

We use the panel regression specification because it boosts the power of our statistical analysis by allowing us to exploit both cross-sectional and time-series variations in country-level portfolio returns and country-level predictors. Since the number of coefficient estimates in our model (9 in the baseline model, 20 with the dummies) exceeds the number of cross-sections (5), we are not able to estimate panel regressions with random effects. Therefore, we estimate the pooled (population averaged) model and the fixed effects model using a consistent estimator for our covariance matrix.

4. Empirical Results and Analysis

We run the regression in EViews using the OLS panel data specification, Table 3 presents the estimation output and effects tests.

Table 3: Estimation output and effects tests

Variable	Pooled OLS	Fixed Effects
C	16.88357***	15.99231***
	(4.894)	(4.956557)
INC(-2)	-26.48847	-14.57419
	(44.18449)	(46.01833)
RU(-2)	8.85614**	11.51191**
	(4.3307)	(5.511067)
YHG(-2)	41.83477	53.68242
	(32.27203)	(40.61183)
DIV(-1)	-10.01499	38.28407
	(118.0176)	(144.6783)
INCEU(-2)	-392.5264***	-378.3644***
	(55.64644)	(56.60202)
RUEU(-2)	-24.65793***	-27.36691***
	(7.510572)	(8.495444)
YHGEU(-2)	171.6369***	157.4663***
	(39.10277)	(47.86832)
TERM(-1)	1.295142*	1.292566*
	(0.746971)	(0.753796)
BORROW(-1)	1.230324	1.275453
	(0.847474)	(0.865202)
Crisis	-37.21823***	-36.42596***
	(12.43005)	(12.00095)
INC(-2)* Crisis	113.48	73.31238
	(120.8961)	(125.6258)
RU(-2)* Crisis	-14.44235**	-16.70542**
	(5.687707)	(6.663876)
YHG(-2)* Crisis	-47.83932	-38.94848
	(64.57487)	(67.13811)
DIV(-1)* Crisis	540.2953**	492.7157*
	(244.7162)	(269.3975)
INCEU(-2)* Crisis	-1735.756***	-1737.466***
	(501.8676)	(500.6576)
RUEU(-2)* Crisis	25.7072**	28.43408**
	(11.2335)	(11.90614)
YHGEU(-2)* Crisis	1262.625***	1262.029***
	(134.7689)	(131.9174)
TERM(-1)* Crisis	10.77365***	10.6521***
	(2.267407)	(2.343779)
BORROW(-1)* Crisis	19.83291***	19.84583***
	(1.967409)	(2.01218)
R^2	0.266882	0.268716
Adjusted R^2	0.221212	0.212838
F-Statistic	5.843741	4.808912
Prob(F-statistic)	0.000000	0.000000

Effects Tests	Statistic	Prob.
Cross-section F	0.188787	0.9442
Cross-section Chi-square	0.814339	0.9365

Note. This table presents the estimates of equation (3.5.2) using both pooled OLS and fixed effects models. The standard errors are presented between parenthesis under each estimated coefficient. Statistical significance is represented by * at 10%, ** at 5% and *** at 1%. We aim from this regression to predict country residual returns from a benchmark risk free rate in quarter *t* using lagged variables from quarters *t-1* and *t-2*. *inc*, *ru* and *yhg* are the country level macroeconomic indicators employed from quarter *t-2* and representing income growth, relative unemployment rate and yearly growth in a house price index respectively. *inceu*, *rueu* and *yhgeu* are the same indicators on a Eurozone level, also utilized with a lag of two quarters. *div* is defined as log (1+dividend yield) of country portfolios employed from quarter *t-1*, *term* and *borrow* are the term spread and borrowing spread respectively also lagged by one quarter. *crisis* is a dummy variable that assumes a value of 1 in the financial crisis (2008Q1-2011Q3) and zero otherwise; *crisis* on its own allows us to test the significance of the structural change brought by the crisis, whereas when multiplied by the rest of the variables it allows estimating the coefficient of the predictors and their significance in the period of the crisis exclusively. The last part of the table shows the redundant fixed effects tests performed in the fixed effects model to examine the significance of individuality between the five countries.

The F-statistics and the associated p-values reject the null hypothesis of insignificance in both the pooled OLS and fixed effects models. Thus, the variables we use in the regression specification can jointly predict stock returns in our sample of European countries. The dummy variable *crisis* is statistically significant at a 1% level of significance in both regression specifications which confirms the presence of a structural change in the model during the financial crisis[4].

We use redundant fixed effects tests in the fixed effects model to test the joint significance of the fixed estimates. The statistic values of both F and Chi-square tests as well as the associated p-values fail to reject the null that cross-section effects are redundant indicating that the heterogeneity between the tested countries is insignificant. Therefore, we consider the population-averaged pooled regression model as the main model for our analysis. One alternative is to run the country by country regressions in which all indictors are allowed to have country specific estimates; we estimate those regressions and the results are shown in appendix C. Probability of Wald F-statistic equals zero for all country-level regressions suggesting that the global significance is preserved even when the model is performed for each country individually and corrected for both heteroscedasticity and autocorrelation. We

[4] Appendix B shows the graphs of all the variables we employ, the structural change confirmed by the model is also visible in the graphs.

rely on the pooled regression specification in our analysis instead of the country-level regressions because the pooled model boosts the power of our statistical analysis by allowing us to exploit both cross-sectional and time-series variations in country-level portfolio returns and country-level predictors. Additionally, pooling the observations in a panel data setting solves correlation and small sample problems of country-level regressions, which grants our inference more validity.

Considering the full sample estimates; out of the three main country-level return predictors only relative unemployment *ru* is statistically significant at a 5% level of significance. Both the negative coefficient estimate of country labor income growth *inc* and positive coefficient estimate of country relative unemployment rate *ru* are consistent with the conclusion of Fama and French (1989) that expected returns are higher (lower) when economic conditions are weak (strong). Fama and French (1989) studied the relation between business conditions and expected returns on stocks and bonds and suggested that variations in expected returns are opposite to business cycle conditions. The authors presented the following economic stories for their findings:

i. When income is high (low) investors attempt to smooth their future consumption patterns by saving more (less), this higher (lower) desired saving leads to lower (higher) expected returns in absence of an offsetting increase (decrease) in investment opportunities.
ii. Business condition indicators proxy for risks that are higher (lower) when times are poor (good), therefore securities must offer higher (lower) returns in those times.
iii. Some of the variation in expected returns is generated by the business cycle productivity shocks.

The results we obtain for country-level labor income growth *inc* and country-level relative unemployment rate *ru* confirm the counter-cyclicality of stock returns documented in the U.S. and UK[5]. Higher (lower) labor income reflects stronger (weaker) economic conditions and predicts lower (higher) returns, therefore the estimated coefficient of *inc* assumes a

[5] Fama and French (1989) in the U.S., Velazquez and Smith (2013) in the UK

negative sign. Conversely, higher (lower) unemployment reflects weaker (stronger) economic conditions and predicts higher (lower) returns, therefore the estimated coefficient of *ru* assumes a positive sign.

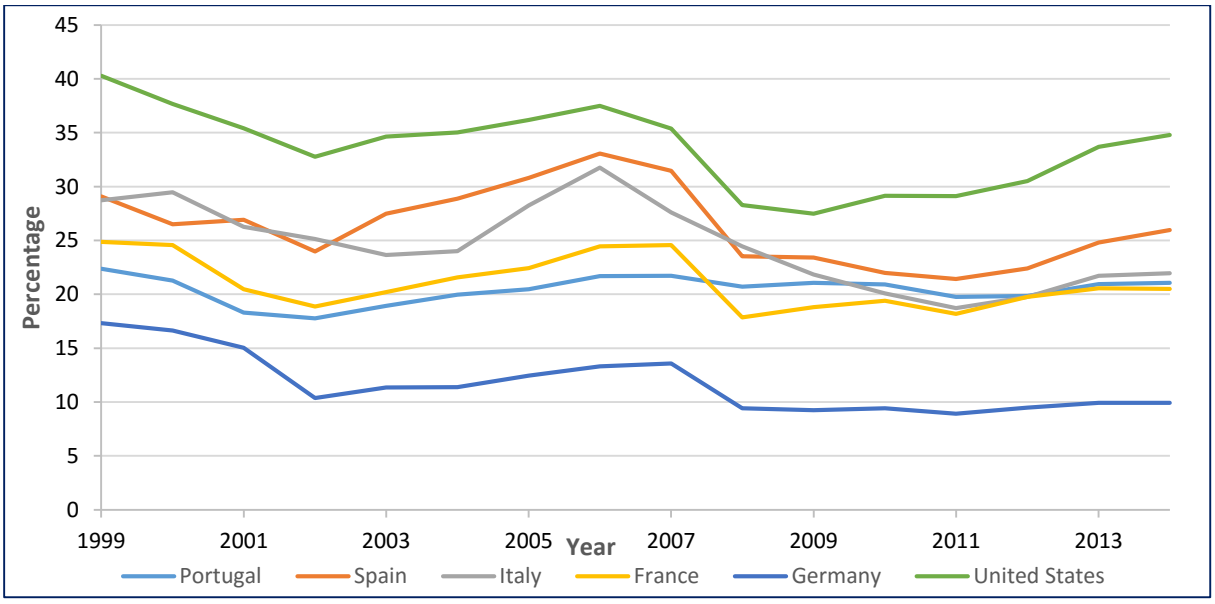
In contrast to the country-level predictors, their analogous Eurozone measures have stronger and more significant estimates. The negative sign of labor income growth is preserved when considering the Eurozone measure whereas the positive sign of relative unemployment is not. We are not able to provide a theoretical framework for these two Eurozone variables similar to the one we provided for their analogous country level measures because our sample does not cover all Eurozone countries; Eurozone economic expansion (contraction) might predict lower (higher) stock returns for Eurozone countries on average, however this does not imply that it should predict lower (higher) stock returns for each subset of Eurozone countries. The variable *yhgeu* we use to capture house price changes in the Eurozone and to proxy for the housing collateral ratio (*hy)* of Lustig and van Nieuwerburgh (2005) has a significantly positive estimate which is theoretically plausible. Lustig and van Nieuwerburgh (2005) reasoned that a decrease in house prices decreases the collateral value of houses which increases investors' exposure to idiosyncratic risk and raises the conditional market price of risk, thus a decline in the U.S. *hy* leads to higher market return. Using the same theoretical framework, we can conjecture that a decline in the Eurozone *hy* leads to higher market return; higher Eurozone market return results in a lower country residual return because the latter is approximately the difference between the raw country return and the market return. This is indeed the case in our model.

The two conclusions we draw from our return predictability regressions are (i) country level business cycle indicators are not robust predictors of country stock returns in Portugal, Spain, Italy, France and Germany, and (ii) the Eurozone counterparts of these indicators incorporate more valuable information about future country-level stock returns in the aforementioned countries. The results of our regressions are exactly the opposite of those obtained by Korniotis and Kumar (2013); the authors found that two of the three main state-level predictors are significant whereas all of their U.S. counterparts are not.

Why country-level business cycle variables fail to predict country returns in our sample of European countries whereas state-level indicators can significantly predict state returns in the U.S.?

The reasoning we provide for this phenomenon is that the percentage of household financial assets (shares and other equity) of total financial assets is much smaller in our sample of European countries when compared to the U.S. In other words, equity market wealth represents a much lower percentage of household's net worth in Portugal, Spain, Italy, France and Germany than in the U.S. Therefore, even when temporary country-level economic fluctuations in the business cycle affect household's investment decisions and alter their required rates of return on financial assets; this effect does not propagate to the stock market because there are not many households who own stocks. Figure 2 shows household shares and other equity as a percentage of total financial assets in the European countries we analyze as well as in the U.S. between the years 1999-2014.

Figure 2: Household shares and other equity, % of total financial assets, 1999-2014



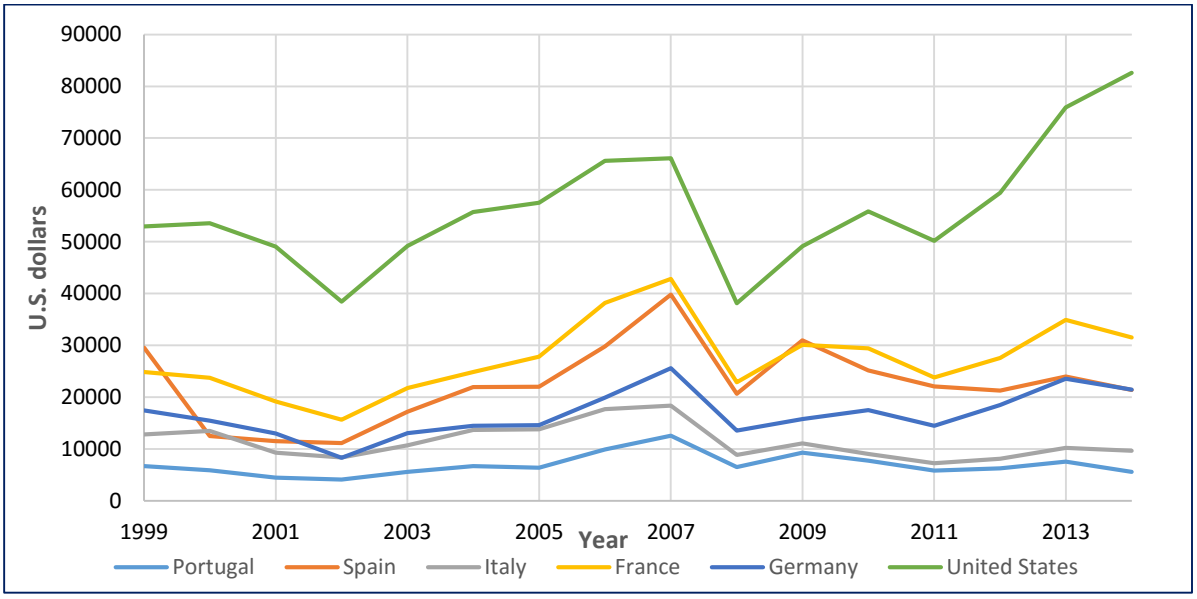
Source. OECD (2016)[6], reproduced.
Note. Figure 2 shows household shares and other equity as a percentage of total financial assets between 1999 and 2014 in Portugal, Spain, Italy, France, Germany and the U.S. We use this figure to show that stock market wealth accounts for a lower percentage of household's net worth in our sample of European countries than in

[6] Data is available at https://data.oecd.org/hha/household-financial-assets.htm.

the U.S. which makes it is harder in those countries for temporary economic fluctuations to propagate to the stock market through household demand shocks.

The portion of shares and other equity owned by households as a percentage of total financial assets is always superior in the U.S. than in our sample of European countries for the whole 1999-2014 period. The superiority in comparing percentage terms reflects even greater and more important superiority when comparing absolute terms because the value of total financial assets in the U.S. is much bigger than in the other countries even after correcting for population differences. To illustrate the size difference, we graph the per capita dollar value of total market capitalization of all domestic listed companies in each of the countries we study as well as in the U.S between the years 1999-2014. Figure 3 shows the results.

Figure 3: Market capitalization of all listed domestic companies, USD/capita, 1999-2014



Source. Author's calculations based The World Bank data[7] (2016).
Note. Figure 3 shows the per capita dollar value of total market capitalization of all domestic listed companies in Portugal, Spain, Italy, France, Germany and the U.S. between the years 1999-2014. We multiply annual values of total market capitalization of listed domestic companies (% of GDP) by the annual GDP per capita in each of the countries to get the per capita market capitalization. The findings of figures 2 and 3 indicate that stock market wealth accounts for a much higher percentage of household's net worth in the U.S. than in Portugal, Spain, Italy, France and Germany. Because both the percentage of total financial assets owned by households in the form of equity (figure 2) and the per capita value of available equity (figure 3) are superior in the U.S.

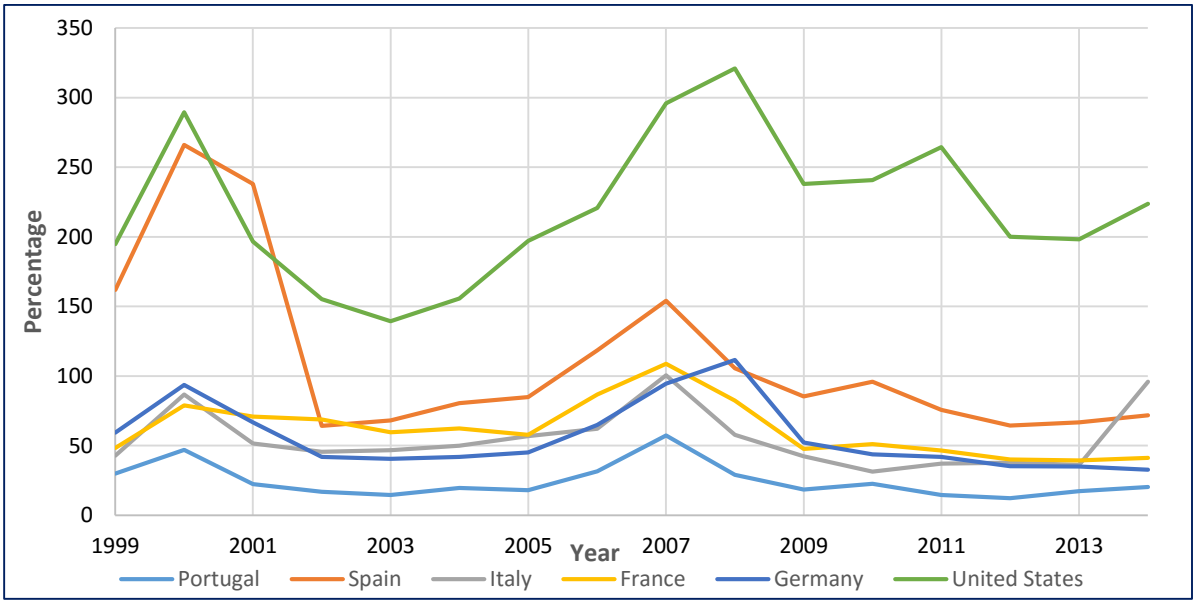
[7] Data is available at:
http://beta.data.worldbank.org/?end=2014&indicators=CM.MKT.LCAP.GD.ZS&start=1999 and
http://beta.data.worldbank.org/?end=2014&indicators=NY.GDP.PCAP.CD&start=1999

The reasoning we just presented is similar to the one used by Hamburg et al. (2005) to justify the contradiction between their findings in Germany and findings of analogous studies in the U.S., UK and Australia. Hamburg et al. (2005) found that the consumption-wealth (*cay)* ratio fails to predict stock market fluctuations in German data, which contradicts the robust and well-documented forecasting power of *cay* in the Anglo-Saxon economies (e.g. Lettau and Ludvigson (2001) in the U.S., Fernandez-Corugedo et al. (2003) in the UK). The authors concluded the following:

"But whereas earlier studies for the U.S., Australia and the UK have documented that this cointegrating relationship predicts changes in asset prices, in particular risk premia in the stock market, we find that cay mainly predicts income changes in German data. Our explanation for this phenomenon is that stock market wealth accounts for a much smaller share of household net worth in Germany than in the Anglo Saxon economies so that temporary fluctuations in stock markets have only very limited impact on German private household net worth. We have interpreted this observation in the light of well-documented structural differences in the financial and pension systems of continental Europe and the Anglo-Saxon economies." (Hamburg et al., 2005, p. 23)

One can argue that if households cannot drive prices when local economic conditions fluctuate, other local stock owners (e.g. institutional investors) should be able to affect stock prices especially that our sample of European countries fulfil the criterion of high local stock ownership. The evidence we find so far does not seem to support this argument because: (i) local economic indicators are not statistically significant predictors of local stock returns and (ii) the trading activity is lower in our sample of European economies than in the U.S. This is illustrated in figure 4.

Figure 4: Total value of stocks traded, % of GDP, 1999-2014



Source. The World Bank[8] (2016), reproduced.
Note. Figure 4 shows the total value of stocks traded as a percentage of GDP in Portugal, Spain, Italy, France, Germany and the U.S. We use this figure to show that the trading activity is lower in our sample of European economies than in the U.S. Therefore, it is less likely that the predictable patterns we detect in stock returns are induced by trading shocks.

The total value of stocks traded is superior in the U.S. to that in our sample of European countries, hence it is less likely that the predictable patterns we detect in stock returns are induced by trading shocks. However, even if we assume that the predictable patterns in country stock returns are generated by the current trading activity, this trading does not seem to be caused by country level fluctuations in the business cycle. On the contrary, the evidence we find suggests that if this is the case then it is induced by fluctuations in the Eurozone business cycle because Eurozone indicators are much more significant predictors of country stock returns than their country-level counterparts. This contradicts the findings of Korniotis and Kumar (2013) that U.S. indicators are usually insignificant and weaker than their state analogous measures.

[8] Data is available at: http://beta.data.worldbank.org/?indicators=CM.MKT.TRAD.GD.ZS

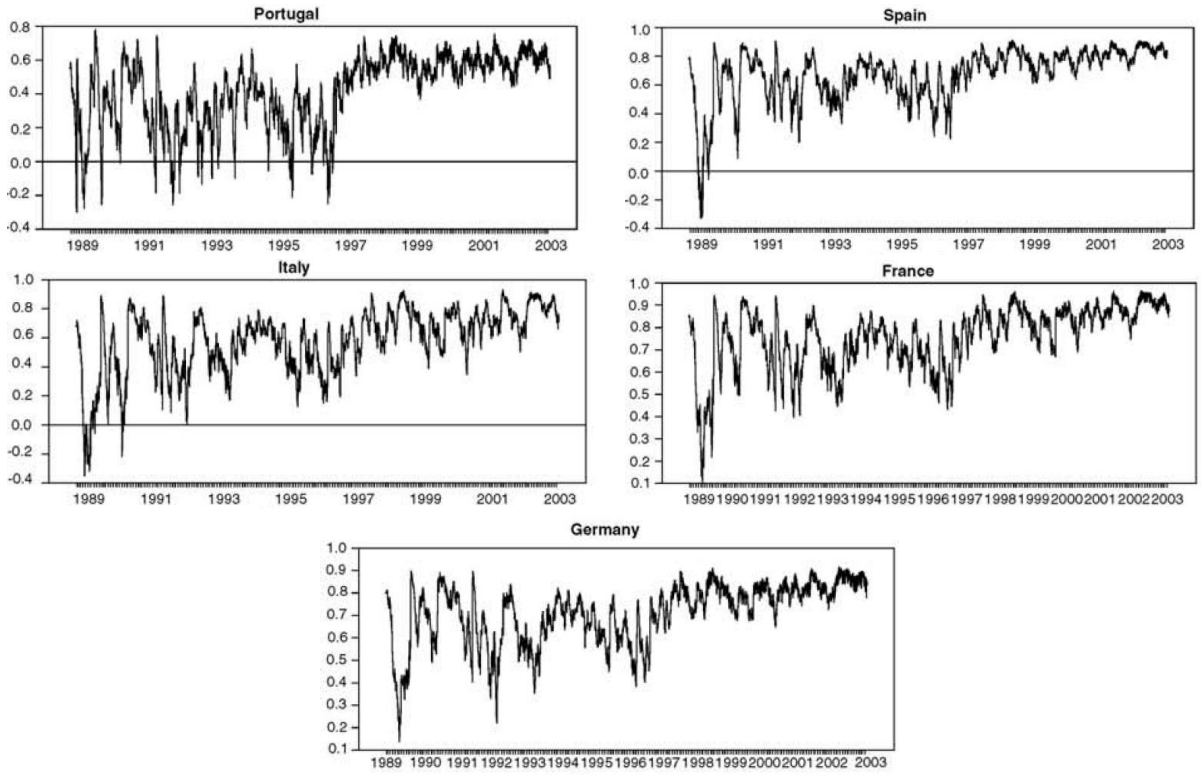
Why can aggregate Eurozone business cycle variables significantly predict country-returns in our sample of European countries whereas aggregate U.S. indicators fail to predict state returns as documented by Korniotis and Kumar (2013)?

The period covered by our study was marked by several economic developments that granted EU indicators more significant predictive power than their country-level counterparts. In particular: (i) the macroeconomic and financial convergence associated with introducing the euro as a single currency on the first of January 1999, (ii) the increase in regional equity bias to the detriment of home bias associated with the same event and (iii) the increased financial contagion[9] phenomenon caused by the dotcom bubble[10], global financial crisis and European debt crisis.

Financial and economic convergence of the Eurozone economies in the late 90s is a highly documented phenomenon. Kim et al. (2005) studied the Eurozone stock markets integration and found that both return and volatility spillovers hiked during the period featured by introducing the euro as a single currency, they documented evidence of increased stock market comovements and showed that much of this increase is caused by the macroeconomic convergence brought by adopting the euro as a single currency. Figure 5 shows the time varying conditional correlations estimated by the authors using bivariate EGARCH models; the correlations measure comovements as well as integration between country index returns and the EMU regional core for Portugal, Spain, Italy, France and Germany.

[9] Financial contagion is defined as the transmission of a shock in excess of what can be explained by economic fundamentals (Pritsker, 2001).
[10] The dotcom started to burst in March 2000 which is around the start of our sample.

Figure 5: Time varying correlations and stock market integration, 1989-2003



Source. Kim et al. (2005), reproduced.

Note. Figure 5 shows the time varying conditional correlations used by the authors to measure comovements and integration of the underlying stock index returns in Portugal, Spain, Italy, France and Germany with the EMU (European Monetary Union) regional core. Countries with high market capitalization such as Germany, France and Italy appear to be more integrated because their conditional correlations assume relatively higher values. The shift in 1996-1997 that sparked a rapid increase in integration coincided with the final stages of Amsterdam treaty aiming to help EU countries fulfil amendments to the Maastricht treaty (Kim et al., 2005).

Hardouvelis et al. (2006) conjectured that the harmonization efforts by EU countries to fulfil the Maastricht criteria for joining the Eurozone have led to both nominal and real convergence of European economies; nominal convergence is the progressive convergence of long-term interest rates and inflation towards German levels, whereas real convergence is the increased business cycle synchronization across European economies. The synchronization in business cycles could have induced higher inter-country correlations in the expected component of real corporate earnings according to the authors. Therefore, we conjecture that the European Monetary Union policies aiming to converge the European economies as well introducing the euro as a single currency have granted the Eurozone indicators a significant predictive and explanatory power of country stock returns.

In addition to the macroeconomic convergence and increased stock market comovements, the introduction of the euro was accompanied by an increase in regional bias to the detriment of home bias for euro area countries which made European investors more exposed to regional indicators. Table 4 shows the equity home bias as well as the regional bias towards EU-13 equities for Portugal, Spain, Italy, France and Germany in 1997, 2001 and 2004.

Table 4: Equity home bias and regional bias towards EU-13 equities, 1997, 2001 & 2004

	Equity Home bias			Regional Bias Towards EU-13 Equities		
	1997	2001	2004	1997	2001	2004
Portugal	0.94	0.89	0.85	0.33	0.65	0.80
Spain	0.95	0.89	0.93	0.33	0.72	0.73
Italy	0.89	0.80	0.85	0.53	0.48	0.52
France	0.90	0.85	0.79	0.48	0.59	0.74
Germany	0.83	0.77	0.77	0.55	0.59	0.62

Source. Schoenmaker and Bosch (2008), reproduced.
Note. Table 4 shows the equity home bias levels as well as the levels of regional bias towards EU-13 equities for Portugal, Spain, Italy, France and Germany. Unlike the decrease in equity home bias, the increase in regional bias towards EU-13 equities was much more profound and permanent. We suggest that the increase in regional bias and the relative decrease in home bias has contributed to granting regional indicators a more significant role in predicting country-level returns than their analogous country-level measures.

Table 5 presents an alternative approach to highlight the increase in regional exposure associated with introducing the euro as a single currency. It shows the share of EMU (European economic and monetary union) equities in the foreign and total portfolios of Portugal, Spain, Italy, France and Germany in the years 1997, 2001 and 2005.

Table 5: Share of EMU equities in country foreign and total portfolios, 1997, 2001 & 2005

	EMU Equities in Foreign Portfolio			EMU Equities in Total Portfolio		
	1997	2001	2005	1997	2001	2005
Portugal	0.540	0.655	0.683	0.077	0.121	0.175
Spain	0.456	0.542	0.733	0.042	0.075	0.14
Italy	0.539	0.642	0.721	0.121	0.231	0.303
France	0.390	0.511	0.505	0.066	0.100	0.160
Germany	0.626	0.596	0.700	0.134	0.183	0.276

Source. De Santis and Gérard (2009), reproduced.
Note. Table 5 shows the share of EMU equities in foreign and total country portfolios for the countries included in our sample. Introducing the euro as a single currency in the year 1999 sparked an increasing trend in investor's holdings of EMU equities and increased investors' exposure to the Eurozone economic conditions.

The second reason we provide for our findings is that, during the period covered by our study, the Eurozone has witnessed several crises resulting in an increased financial contagion between its economies. Kenourgios et al. (2009) examined the time-varying correlation in European equity and bond markets (Euro Area, the Balkans and Central Europe) and found an increase in the dependence level during the dotcom bubble. Samitas and Tsakalos (2013) studied stock market contagion in a sample of eight European countries (including all the five countries we analyze) and found that the subprime crisis has increased the correlation between stock returns, whereas the Greek debt crisis has had a lower effect on those correlations. Similarly, Kazi et al. (2014) used a multivariate asymmetric dynamic conditional correlation model to study shift-contagion in the stock returns of 16 OECD countries (including four out of the five countries we analyze) during the global financial crises and the European debt crisis, their findings confirmed shift-contagion in the former but found no strong evidence during the latter.

The financial contagion phenomenon and the increased correlation between equity returns in the Eurozone economies induced by the dotcom bubble, the global crisis and to a lesser extent the Greek debt crisis have given the Eurozone economic indicators a more important role in predicting country-returns than their country-level counterparts. This is illustrated in the estimation output presented in the beginning of the section; most of the Eurozone indicators preserve signs and become more significant in the financial crisis whereas all of the country-level indicators reverse signs[11]. Therefore, we conjecture that the global financial crisis has weakened the predictive power of country-level indicators and strengthened that of the Eurozone ones. Korniotis and Kumar (2013) documented an opposing evidence in the U.S. partially because their sample covers the period 1983-2008 and thus misses the financial crisis. Korniotis (2008) showed that it is more rational to describe the U.S. economy as a collection of 50-state investors rather than one U.S. level investor because some state-specific risks are not fully shared across states, that does not seem to be the case with the Eurozone

[11] The country variable *div* defined as log (1+dividend yield) of country portfolios becomes positive and statistically significant, which is consistent with the literature (e.g., Campbell and Shiller (1988)).

economies in the 1999-2015 period considering the progressive shocks and policies targeting more economic and financial convergence.

5. Conclusion

In this study, we derive the return series of value weighted country portfolios for Portugal, Spain, Italy, France and Germany. Then we compute the residual return from a benchmark market risk free rate to examine whether country-level stock returns exhibit predictable business cycle patterns that can be potentially exploited. We find evidence suggesting that country-level business cycles fail to predict stock returns whereas aggregate Eurozone business cycles demonstrate a significant predictive ability for country-level equity residual returns.

Our results contradict those of analogous studies performed in the U.S. Korniotis and Kumar (2013) found that state-level business cycles can significantly predict state-stock returns whereas aggregate U.S. level cycles cannot. We present two main economic justifications for this contradiction. First, stock market wealth accounts for a much lower percentage of households' net worth in continental Europe than in the U.S., therefore, it is harder for short-run economic fluctuations to propagate to the stock market even if they affect households' investment decisions. Second, the period covered by our study was marked by several economic developments that granted EU indicators more significant predictive power than their country-level counterparts. In particular: (i) introducing the euro as a single currency on the first of January 1999 which led to macroeconomic and financial convergence of Eurozone economies as well as to a higher regional equity bias to the detriment of home bias of European investors and (ii) the increased financial contagion phenomenon between EU equity markets induced by the dotcom bubble, global financial crisis and to a lesser extent the European debt crisis. We present those justifications in the light of well-documented structural differences in the equity ownership structure between the economies of continental Europe and the U.S. as well as the evidence of economic and financial convergence and increased regional equity bias between the EU economies within the 1999-2015 period.

The study has significant contributions to the literature because it is, to the best of our knowledge, the first to examine predictable business cycle swings of stock returns in continental Europe. Despite the relevance of the topic and the abundant evidence in the UK

and the U.S. the literature seems to lack evidence from continental Europe, our study partially fills this gap.

Our findings have significant implications for investors using macroeconomic trading strategies to time the European equity markets because we find evidence suggesting that Eurozone business cycle indicators incorporate more valuable information about future country-level returns than their country-level counterparts. Therefore, investors should rely more on Eurozone indicators in timing the European equity markets.

We have several suggestions for future research. First, it is intriguing (though challenging) to increase the sample size of the study by including all Eurozone economies in the analysis regardless of the local equity ownership criterion. Second, it is also interesting to extend the sample for the countries in which economic data are available for a longer time span, then analyze the responsiveness of equity returns to country and regional business cycles before and after adopting the euro as a single currency in the 1999. Finally, data to calculate the cay ratio are available for Spain through FEP databases, therefore it is possible to analyze the predictive power for the cay ratio in Spain and compare the results with similar studies done in the U.S., UK and Germany[12].

[12] Lettau and Ludvigson (2001) in the U.S., Fernandez-Corugedo et al. (2003) in the UK and Hamburg et al. (2005) in Germany.

References

Balta, N., & Delgado, J. (2009). Home Bias and Market Integration in the EU. CESifo Economic Studies, 55(1), 110-144.

Balvers, R. J., Cosimano, T. F., & McDonald, B. (1990). Predicting Stock Returns in an Efficient Market. The Journal of Finance, 45(4), 1109-1128.

Bodie, Z. (1976). Common Stocks as a Hedge Against Inflation. The Journal of Finance, 31(2), 459-470.

Boudoukh, J., Michaely, R., Richardson, M., & Roberts, M. (2007). On the Importance of Measuring Payout Yield: Implications for Empirical Asset Pricing. The Journal of Finance, 62(2), 877–915.

Campbell, J. Y. (1996). Understanding Risk and Return. Journal of Political Economy, 104(2), 298-345.

Campbell, J. Y., & Cochrane, J. H. (1999). By Force of Habit: A Consumption-Based Explanation of Aggregate Stock Market Behavior. Journal of Political Economy, 107(2), 205-251.

Campbell, J. Y., & Shiller, R. J. (1988). Stock Prices, Earnings, and Expected Dividends. The Journal of Finance, 43(3), 661-676.

Campbell, J. Y., & Shiller, R. J. (1988). The dividend-price ratio and expectations of future dividends and discount factors. The Review of Financial Studies, 1(3), 195-228.

Campbell, J. Y., & Yogo, M. (2006). Efficient tests of stock return predictability. Journal of Financial Economics, 81(1), 27–60.

CEPR (2016). October 2015 – Euro Area Out of Recession, in Unusually Weak Expansion. http://cepr.org/content/euro-area-business-cycle-dating-committee, accessed on 11 April 2016.

Chan, L. K., Hamao, Y., & Lakonishok, J. (1991). Fundamentals and Stock Returns in Japan. The Journal of Finance, 46(5), 1739-1764.

Chordia, T., & Shivakumar, L. (2002). Momentum, Business Cycle, and Time-Varying Expected Returns. The Journal of Finance, 57(2), 985-1019.

Cochran, J. H. (1991). Production-Based Asset Pricing and the Link Between Stock Returns and Economic Fluctuations. The Journal of Finance, 46(1), 209-237.

Cochrane, J. H. (2008). The Dog That Did Not Bark: A Defense of Return Predictability. The Review of Financial Studies, 21(4), 1533-1575.

Cooper, M., Gutierrez, R. V., & Marcum, B. (2005). On the Predictability of Stock Returns in Real Time. The Journal of Business, 78(2), 469-500.

Cowles, A. (1933). Can Stock Market Forecasters Forecast? Journal Of The Econometric Society, 1(3), 309-324.

Davydoff, D., Fano, D., & Qin, L. (2013). Who Owns the European Economy? Evolution of the Ownership of EU-Listed Companies Between 1970 and 2012. European Commission .

De Santis, R. A., & Gérard, B. (2009). International portfolio reallocation: Diversification benefits and European monetary union. European Economic Review, 58(8), 1010-1027.

Doukas, J. A., Kim, C. F., & Pantzalis, C. (2006). Divergence of Opinion and Equity Returns. The Journal of Financial and Quantitative Analysis, 41(3), 573-606.

Dow, C. H. (1920). Scientific Stock Speculation. New York: The Magazine of Wall Street.

Durham, J. B. (2003). Monetary Policy and Stock Price Returns. Financial Analysts Journal, 59(4), 26-35.

Edmans, A., Garcia, D., & Norli, Ø. (2007). Sports Sentiment and Stock Returns. The Journal of Finance, 62(4), 1967-1998.

Eleswarapu, V. R., & Reinganum, M. R. (2004). The Predictability of Aggregate Stock Market Returns: Evidence Based on Glamour Stocks. The Journal of Business, 77(2), 275-294.

Fama, E. F. (1981). Stock Returns, Real Activity, Inflation, and Money. The American Economic Review, 71(4), 545-565.

Fama, E. F. (2013). Two Pillars of Asset Pricing. Nobel Prize lecture available at https://www.nobelprize.org/nobel_prizes/economic-sciences/laureates/2013/fama-lecture.pdf.

Fama, E. F., & French, K. R. (1989). Business Conditions and Expected Returns on Stocks and Bonds. Journal of Financial Economics, 25(1), 23-49.

Fama, E. F., & French, R. K. (1988). Dividend Yields and Expected Stock Returns. Journal of Financial Economics, 22(1), 3-25.

Fama, E. F., & Schwert, G. W. (1977). Asset Returns and Inflation. Journal of Financial Economics, 5, 115-146.

Fernandez-Corugedo, E., Price, S., & Blake, A. (2003). The dynamics of consumers' expenditure: the UK consumption-ECM redux. Bank of England Working Paper 204.

Ferson,, W. E., Sarkissian, S., & Simin, T. T. (2003). Spurious Regressions in Financial Economics? The Journal of Finance, 58(4), 1393-1413.

Fisher, I. (1930). The Theory of Interest. New York: Macmillan.

French, K. R., Schwert, G. W., & Stambaugh, R. F. (1987). Expected Stock Returns and Volatility. Journal of Financial Economics, 19(1), 3-39.

Goetzmann, W. N., & Jorion, P. (1993). Testing the Predictive Power of Dividend Yields. Journal of Finance, 48(2), 663-679.

Goyal, A. (2004). Demographics, Stock Market Flows, and Stock Returns. The Journal of Financial and Quantitative Analysis, 39(1), 115-142.

Hamburg, B., Hoffmann, M., & Keller, J. (2005). Consumption, Wealth and Business Cycles in Germany. CESifo Working Paper Series No. 1443.

Hardouvelis, G. A., Malliaropulos, D., & Priestley, R. (2006). EMU and European Stock Market Integration. The Journal of Business, 79(1), 365-392.

Hjalmarrsson, E. (2010). Predicting Global Stock Returns. The Journal of Financial and Quantitative Analysis, 45(1), 49-80.

Hong, H., Kubik, J. D., & Stein, J. C. (2008). The Only Game in Town: Stock-Price Consequences of Local Bias. Journal of Financial Economics, 90(1), 20–37.

Huang, R. D., & Stoll, H. R. (1994). Market Microstructure and Stock Return Predictions. The Review of Financial Studies, 7(1), 179-213.

Jaffe, J. F., & Mandelker , G. (1976). The "Fisher Effect" for Risky Assets: An Empirical Investigation. The Journal of Finance, 31(2), 447-458.

Jagannathan, R., & Wang, Z. (1996). The Conditional CAPM and the Cross-Section of Expected Returns. The Journal of Finance, 51(1), 3-53.

Kazi , A. I., Mehanaoui , M., & Akbar , F. (2014). The shift-contagion effect of global financial crisis and the European debt crisis on OECD Countries . Ipag Business School Working Paper No. 2014-128.

Kenourgios , D., Samitas , A., & Paltalidis , N. (2009). Financial Market Dynamics in an Enlarged European Union. Journal of Economic Integration, 24(2), 197-221.

Kim, S. J., Moshirian, F., & Wu, E. (2005). Dynamic stock market integration driven by the European Monetary Union: An empirizal analysis. Journal of Banking & Finance, 29(10), 2475–2502.

Korniotis, G. M. (2008). Habit Formation, Incomplete Markets, and the Significance of Regional Risk for Expected Returns. The Review of Financial Studies, 21(5), 2139-2172.

Korniotis, G. M., & Kumar, A. (2013). State-Level Business Cycles and Local Return Predictability. The Journal of Finance, 733-761.

Lanne, M. (2002). Testing the Predictability of Stock Returns. The Review of Economics and Statistics, 84(3), 407-415.

Lettau, M., & Ludvigson, S. (2001). Consumption, Aggregate Wealth, and Expected Stock Returns. The Journal of Finance, 645-670.

Lettau, M., & Nieuwerburgh, S. V. (2008). Reconciling the Return Predictability Evidence. The Review of Financial Studies, 21(4), 1607-1652.

Lustig, H. N., & Van Nieuwerburgh, S. G. (2005). Housing Collateral, Consumption Insurance, and Risk Premia: An Empirical Perspective. The Journal of Finance, 60(3), 1167-1219.

Mankiw, G. N., & Shapiro, M. D. (1986). Do We Reject Too Often? Economics Letters, 20(2), 139-145.

Miller, E. M. (1977). Risk, Uncertainty, and Divergence of Opinion. The Journal of Finance, 32(4), 1151-1168.

Mukherji, S., Dhatt, M. S., & Kim, Y. H. (1997). A Fundamental Analysis of Korean Stock Returns. Financial Analysts Journal, 53(3), 75-80.

Neal, R., & Wheatley, S. M. (1998). Do Measures of Investor Sentiment Predict Returns? The Journal of Financial and Quantitative Analysis, 33(4), 523-547.

Nelson, C. R. (1976). Inflation and Rates of Return on Common Stocks. The Journal of Finance, 31(2), 471-483.

OECD (2016). Household financial assets (indicator). doi: 10.1787/7519b9dc-en, accessed on 15 April 2016.

Patelis, A. D. (1997). Stock Return Predictability and The Role of Monetary Policy. The Journal of Finance, 1951-1972.

Pirinsky , C., & Wang, Q. (2006). Does Corporate Headquarters Location Matter for Stock Returns? The Journal of Finance, 61(4), 1991-2015.

Priestley, R. (1997). Seasonality, Stock Returns and the Macroeconomy. The Economic Journal, 107(445), 1742-1750.

Pritsker, M. (2001). The Channels for Financial Contagion. In S. Claessens, & K. Forbes, International Financial Contagion (pp. 67-95). New York: Springer US.

Samitas, A., & Tsakalos, I. (2013). How can a small country affect the European economy? The Greek contagion phenomenon. Journal of International Financial Markets, Institutions & Money, 25, 18-32.

Schoenmaker, D., & Bosch , T. (2008). Is the Home Bias in Equities and Bonds Declining in Europe? Investment Management and Financial Innovations, 5(4), 90-102.

Schoenmaker, D., & Soeter, C. (2014). New Evidence on the Home Bias in European Investment. Amsterdam: Duisenberg School of Finance .

Sousa, R. M. (2010). Consumption, (dis)aggregate wealth, and asset returns. Journal of Empirical Finance, 606-622.

Stambaugh, R. F. (1986). Bias in Regression with Lagged Stochastic Regressors. CRSP Working Paper N0. 156, University of Chicago.

Thorbecke, W. (1997). On Stock Market Returns and Monetary Policy. The Journal of Finance, 52(2), 635-654.

Velazquez, A. M., & Smith, P. N. (2013). Equity Returns and the Business Cycle: The Role of Supply and Demand Shocks. CAMA Working Paper Series Paper 22/2013.

Watts, D. G. (1880). Speculation as a Fine Art and Thoughts on Life. New York: Traders Press.

Wolf, M. (2000). Stock Returns and Dividend Yields Revisited: A New Way to Look at an Old Problem. Journal of Business & Economic Statistics, 18(1), 18-30.

Yogo, M. (2006). A Consumption-Based Explanation of Expected Stock Returns. The Journal of Finance, 61(2), 539-580.

Appendices

Appendix A – Portfolios' Specifications

Table 6: Identifiers of excluded stocks

Portugal	Spain	Italy	France				Germany		
FENU.LS	ALCE.SCT	CUCI.MI	AUER.PA	MLCTA.PA	ALGAU.PA	MLCLP.PA	ADLG.DE	DNIG.BE	SYWGn.BE
COPM.LS	S1023.MC	ITPG.PK	CHFP.PA	QTE.PA	VIA.PA	MLMNR.PA	BFIG.BE	HZHG.BE	5TRG.H
TRAAP.LS	S0314.MC	ALWOO.PA	FINM.PA	EDDS.PA	LTWN.SI	MLCSV.PA	KWGG.DE	IRPG.H	BGZG.H
CDUL.LS	FOBE.SCT	YIV.MI	CROS.PA	ATAR.PA	MLEDU.PA	MLCMI.PA	HABG.DE	BG1An.BE	BEZ.DE
AGDCU.LS	GAES.SCT	SOST.PK	DVSP.PA	ALGEP.PA	MLCHE.PA	MLAKD.PA	BHSG.F	EUE15PEX.L	MMH.H
ALISA.LS	S2293.MC	MLAZL.PA	LFVE.PA	DPTP.PA	LYXLEM.PA	MLERI.PA	MTVG.DE	RUCG.MU	MLECO.PA
ALNOR.LS	S0987.MC	MLMCE.PA	FAUV.PA	REGR.PA	MLFCI.PA	MLSIL.PA	MUKG.F	SU3G.BE	RE0.D
	S2975.MC	MLFIH.PA	FFBP.PA	PATC.PA	BVI.PA	MLONL.PA	NAKG.H	D2BG.BE	ZEITg.F
	UCAV.SCT	MLEBX.PA	FCCH.PA	CJSP.PA	MLVST.PA	MLVOV.PA	PKBG.F	P4OG.DE	SXMUUSD.DE
	S2418.MC	MLLB.PA	CRPP.PA	RDGP.PA	MLMAI.PA	MLAMA.PA	RKBG.F	I8CKk.H	S26G.D
	S0239.MC	MLSMP.PA	RXPA.PA	ROUC.PA	MLTRS.PA	MLNOT.PA	SWAG.DE	MLPRO.PA	ETPGg.F
	S1707.MC	MLSNT.PA	GMDS.PA	ARTE.PA	MLARI.PA	MLGAL.PA	SING.F	IR1.MU	RUSSINAVEUR.DE
	S2913.MC	MLHTT.PA	AREIT.PA	PNOV.PA	MLETA.PA	MLANT.PA	SPRGn.DE	SXAREX.L	VUAG.D
	S2962.MC	EMCC.MI	FSDV.PA	FORG.PA	ALAST.PA	MLPSH.PA	ZILGn.DE	SXFREX.L	7PVG.H
	CLEO.MC		SCMX.PA	AUCP.PA	MLPVG.PA	ALSFT.PA	SGSG.D	SXIREX.L	28LG.H
	ISUR.MC		MRM.PA	AMOS.PA	MLEAV.PA	NANOB.PA	HRPKk.DE	SXKREX.L	SAXG.DE
	BOBI.SCT		TYNN.PA	ALCES.PA	ALROC.PA	MLACT.PA	EFSG.MU	SXMREX.L	RNM.F
	S2864.MC		EFEP.PA	JAJP.PA	MLABO.PA	MLAFT.PA	COPMa.DE	SXNREX.L	7PR.F
	S1060.MC		TWVG.PA	PRSW.PA	LVC.PA	MLSOC.PA	SXDEEX.L	SXOREX.L	BEUT.PK
	S1350.MC		BLBP.PA	ITXA.PA	MLTHA.PA	MLIFC.PA	BMMG.DE	SXPREX.L	STOXX50ENAV.DE
	S2594.MC		MDEL.PA	STID.PA	MLMTD.PA	MLCET.PA	NWXG.DE	SXQREX.L	BNNn.DE
	S2148.MC		VDPS.PA	NR21.BR	MLNES.PA	MLDDP.PA	SD1.DE	SXRREX.L	SHVA.DE
	MNSA.SCT		KRNI.PA	KZBO.PA	LMAL.SI	MLCOL.PA	UBKG.MU	SXTREX.L	FTSEEX.L
	S1692.MC		MCLC.PA	CARPD.PA	MLJSA.PA	MLJAN.PA	ADWG.H	SX3REX.L	AMMG.D
	RONS.SCT		ARDPa.PA	DPUY.PA	ALACR.PA	MLTBM.PA	BIWG.DE	SX7REX.L	MUXG.DE
	S3094.MC		EFIN.PA	DRIS.PA	ALTXC.PA	ETZ.PA	EMH1k.DE	SX8REX.L	
	S2280.MC		CHSS.PA	DJE.PA	ALSOA.PA	MLVIN.PA	CMBGn.F	SX6REX.L	
	S1676.MC		COUP.PA	TNRC.PA	MLRIV.PA	MLEMG.PA	MGUGg.D	SX4REX.L	
	S0720.MC		GRLE.PA	KIMP.PA	MLAMY.PA	FGA.PA	EKKG.BE	NDXEX.DE	
	4PU.F		FNMM.PA	DJTK.PA	CM9.PA	MLPPI.PA	ABAG.DE	DJAPSDEEX.DE	
	YARE.MC		BLEE.PA	ALACI.PA	MLVAN.PA	MLDHZ.PA	BEPG.BE	DJCHOS50EX.DE	
	YPR3.MC		HOIN.PA	MAKE.PA	MLDEX.PA	MLAUD.PA	AAGGn.F	H1IG.SG	
	YHAB.MC		HOMJ.PA	EVER.PA	MLCRO.PA	MLORC.PA	EBKG.DE	E4D.TG	
			HYPB.PA	ALEUP.PA	MLMII.PA	MLHCF.PA	MGNG.DE	L1AG.H	
			IPPP.PA	CHPO.PA	MLACP.PA	MLAGI.PA	MFCG.H	E2NG.MU	
			SIPH.PA	USTE.PA	ALQGC.PA	MLARO.PA	PPAG.DE	W8ZG.F	
			ESTR.PA	ALLOG.PA	MLAAE.PA	ML350.PA	PLEKk.F	SREPEX.L	
			LCLG.PA	PGOA.PA	MLWEY.PA	MLPPF.PA	ELNk.F	M7C.D	
			CBSM.PA	TLDS.PA	MLMGL.PA	MLVAL.PA	CPUGk.F	CDZG.MU	
			NPRI.PA	WTRA.PA	S13.S	MLITG.PA	BYBKk.BE	M5SG.BE	
			PIMP.PA	MLNOV.PA	S5B.S	MLDTB.PA	MYRKk.DE	A3EB.SG	
			PRCH.PA	ALKEY.PA	ALEUA.PA	BBEU.PA	SOOG.MU	NSAG.D	
			TRAM.PA	LOCA.PA	MLKRI.PA	ALIMR.PA	WEG1.DE	APQG.D	
			SIGS.PA	MLTE.PA	ALISC.PA	SMRE.PA	SRWG.H	BIY.MU	
			SPBS.PA	MLCOR.PA	CSWCHF.S	MLOSA.PA	KSWG.F	BLGGgi.F	
			UMHS.PA	MLRAM.PA	MLSIS.PA	MLBRI.PA	BTGGg.F	CVK.D	

VERN.PA	MLATV.PA	MLLEA.PA	ALCYB.PA	VVVGn_p.DE	MADAXGLASNAV.DE
DIGP.PA	MLFER.PA	MLART.PA	BLIM.PA	MDAXIEX.DE	HHXG.H
3CHN.PA	MLOPT.PA	LYSLE.S	MLMAD.PA	SWEGn.DE	3GOK.MU
SECN.PA	WLD.PA	IFNG.L	ALPGG.PA	CCBG.MU	3SQ1.BE
BAUD.PA	ALVIA.PA	LYSSL.S	MLEES.PA	GBQG.H	5BMG.H
MLSCH.PA					

Note. Table 6 shows the list of identifiers of all the stocks we exclude from country portfolios. We retrieve quarterly stock return and market capitalization data for all stocks headquartered in the country and having a minimum market capitalization of 45000 USD from Thomson Reuters Eikon. Return and capitalization values for some of the stocks were inconsistent even retrieved individually; we exclude those stocks from the analysis.

Table 7: Value of market capitalization included in the portfolios

	Retrieved Mkt Cap	Excluded	Included	% Included
Portugal	52,180,188,009.03	192,219,137.55	51,987,968,871.47	99.63162429
Spain	635,179,211,031.93	1,924,571,469.48	633,254,639,562.45	99.69700339
Italy	520,225,558,903.24	357,322,390.79	519,868,236,512.45	99.93131395
France	1,982,406,621,769.33	20,703,535,063.22	1,961,703,086,706.11	98.9556363
Germany	1,816,676,231,951.50	55,632,092,733.98	1,761,044,139,217.52	96.93769909

Note. Table 7 shows the total market capitalization of all filtered companies as well as the value of market capitalization included in each portfolio. The final portfolios represent at least 96% of the total market capitalization of all filtered companies, therefore, the return series we use in this study are representative of the country-level return series and much broader than stock market indices.

Appendix B – Graphs of the Variables

Figure 6: Graph of labor income growth

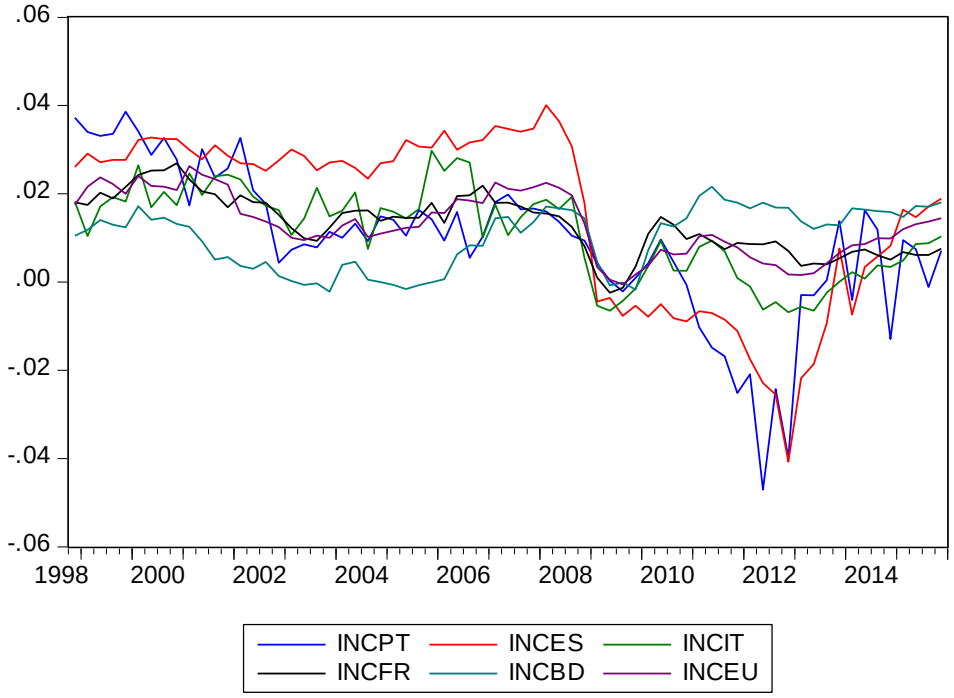


Figure 7: Graph of relative unemployment

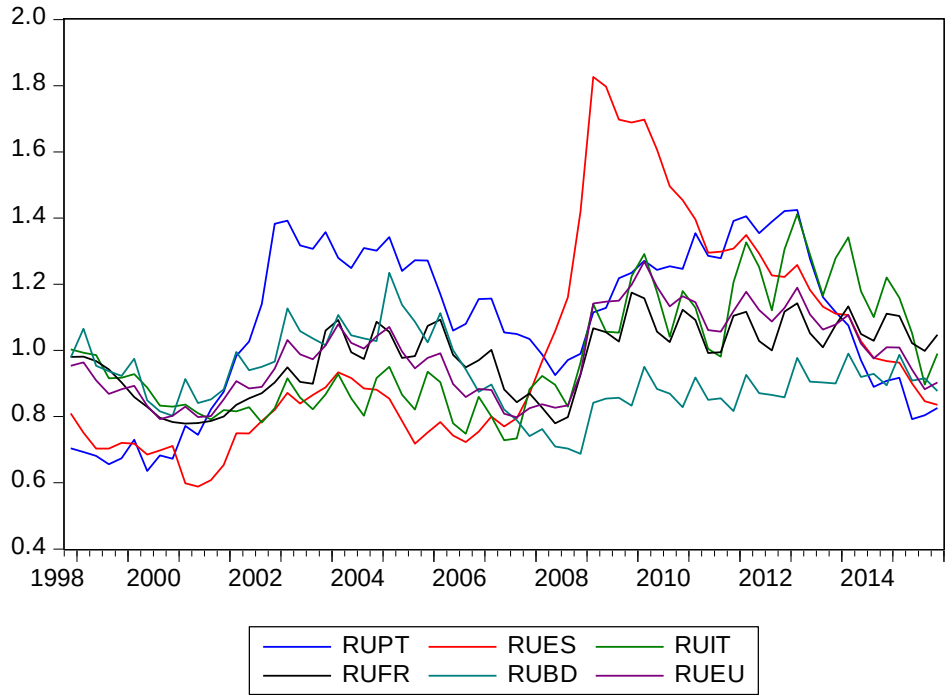


Figure 8: Graph of housing prices growth

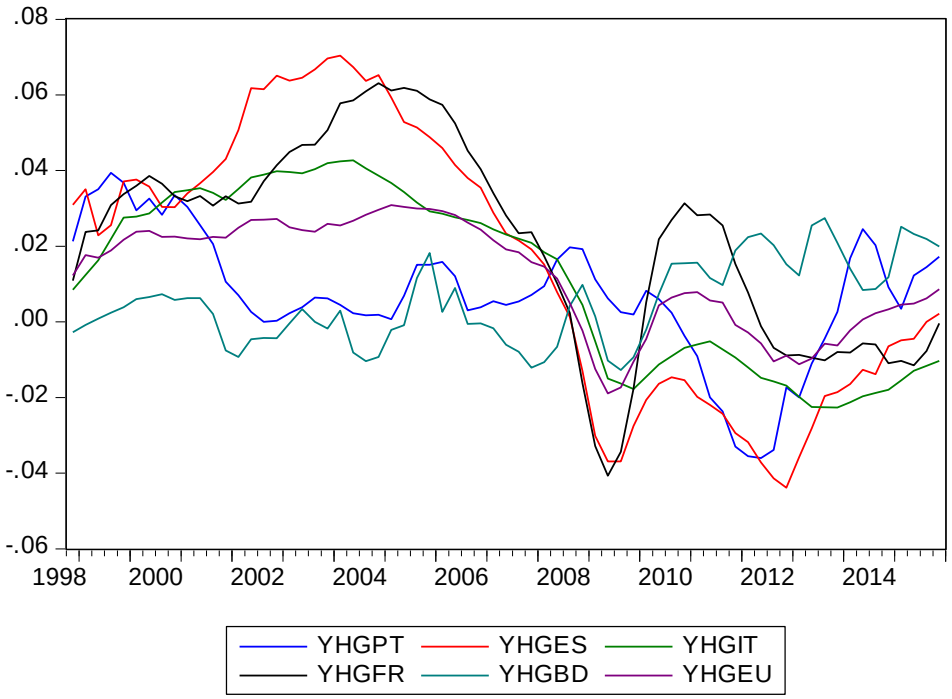


Figure 9: Graph of country-portfolios dividend yield

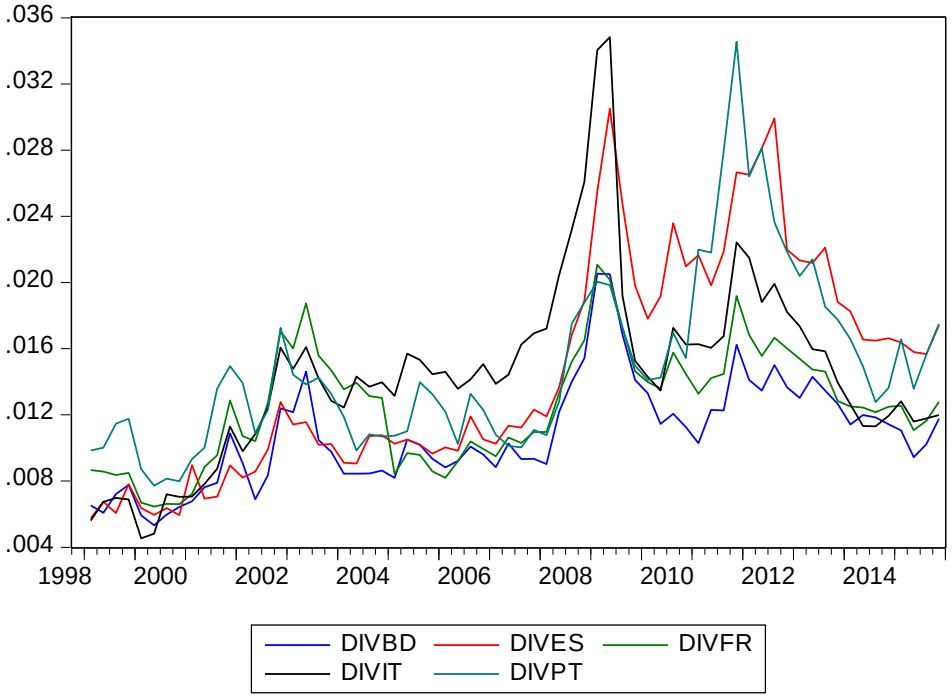
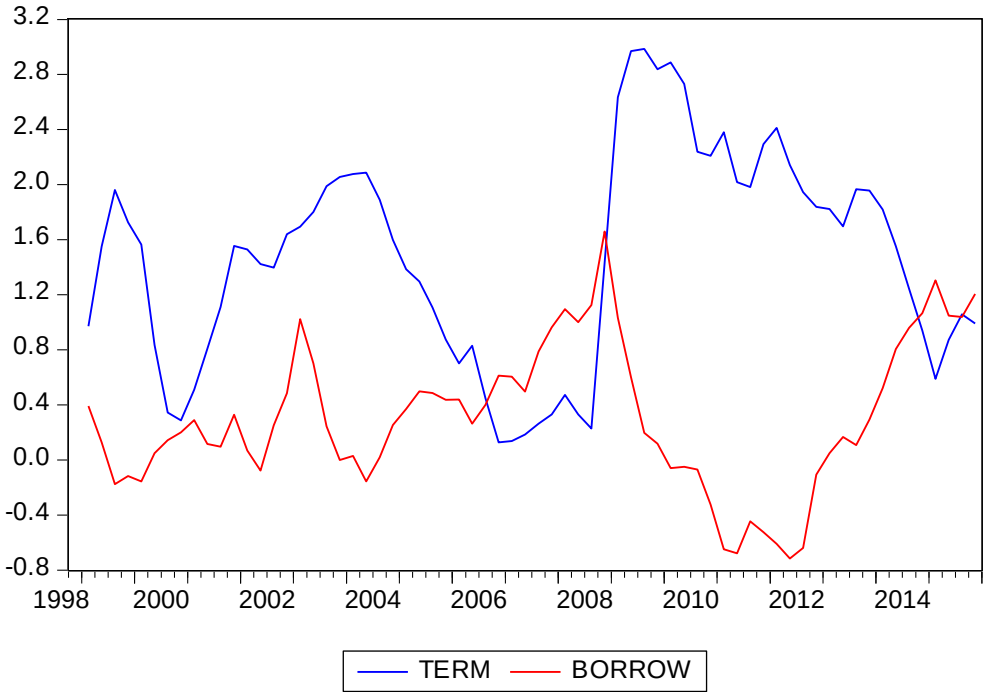


Figure 10: Graph of term and borrowing Spreads



Note. We intend from showing the graphs of all the variables to highlight the structural change brought by the financial crisis. The estimation output shows that this structural shock is substantial because the dummy variable is statistically significant at a 1% level of significance. *inc* represents the growth rate of labor income defined as the log difference of labor income in the current quarter and the same quarter in the previous year. *ru* is relative unemployment calculated as the ratio of the current level of unemployment to the moving average of unemployment rate in the past 16 quarters. *yhg* is the yearly growth in housing prices defined as the log difference between housing prices index value in the current quarter and the same quarter in the previous year. *div* is the control variable capturing dividend yield and defined as log of 1+DY of country portfolios. *term* is the term spread calculated as the return difference between AAA-Eurozone 10-year government bond and AAA-Eurozone 1-year government bond. *borrow* is the borrowing spread defined as the difference between Eurozone average corporate borrowing rate and Eurozone average government long-term bond yields. *inc*, *ru*, *yhg* and *div* are followed by the respective country or Eurozone symbol; PT=Portugal, ES=Spain, IT=Italy, FR=France, BD=Germany and EU=Eurozone.

Appendix C – Country-Level Regressions

Table 8: Country-level regressions, estimation output

	Portugal	Spain	Italy	France	Germany
C	24.78505	7.910683	17.30938	58.22361*	-3.59655
	(38.38592)	(29.75382)	(31.1161)	(31.83704)	(52.14427)
INC(-2)	-135.401	11.50616	-288.458	141.9878	115.4154
	(195.252)	(177.7457)	(251.1144)	(327.2431)	(413.6427)
RU(-2)	36.60921**	-17.572	2.724397	31.22083	-12.686
	(14.08851)	(17.23942)	(19.54987)	(28.07729)	(49.27059)
YHG(-2)	227.3646	93.58786	-141.365	583.6188**	97.88727
	(244.9024)	(144.8898)	(156.6482)	(234.4143)	(315.9117)
DIV(-1)	94.96977	172.0733	-226.593	-307.374	1320.546*
	(277.3237)	(417.9685)	(415.4801)	(332.6759)	(659.0712)
INCEU(-2)	48.11599	-433.807	-252.749	-512.524	-171.68
	(707.4614)	(545.974)	(523.0377)	(407.9636)	(846.8347)
RUEU(-2)	-74.7449**	17.12323	-19.7889	-91.8838*	-5.8325
	(29.33458)	(28.20306)	(31.20424)	(49.75956)	(71.37851)
YHGEU(-2)	-30.3438	-127.174	586.0189	-1023.48**	492.8269
	(175.6075)	(392.7407)	(349.1069)	(508.0412)	(496.558)
TERM(-1)	4.322273	-2.7446	3.139564	6.03746	0.892225
	(4.151591)	(3.157469)	(2.806625)	(3.894174)	(3.737528)
BORROW(-1)	5.620837	-2.67701	-0.95871	7.544699	2.119641
	(4.619898)	(4.187577)	(2.721171)	(5.101514)	(6.623714)
DUMMY	-71.8823	21.60923	-109.83	-174.965***	24.50183
	(60.22672)	(63.89998)	(75.79161)	(63.56631)	(57.63698)
INC(-2)*DUMMY	1149.92	-2415.76	-1451.1	-1436.28	3756.283***
	(756.2871)	(1812.287)	(2345.282)	(1794.686)	(741.7041)
RU(-2)*DUMMY	-63.918	162.3793	25.89019	-141.844	-28.6351
	(59.06549)	(112.8219)	(67.79866)	(127.9317)	(54.4538)
YHG(-2)*DUMMY	-375.537	5161.881**	846.0129	-2154.49	-3281.27***
	(672.4887)	(2092.175)	(1492.674)	(1324.08)	(445.5626)
DIV(-1)*DUMMY	217.4275	1336.345	351.7174	-335.503	3435.049***
	(1006.873)	(1311.924)	(642.0684)	(2006.214)	(741.642)
INCEU(-2)*DUMMY	680.1916	6496.956	-443.53	-1277.15	-9955.19***
	(1401.346)	(3915.013)	(3193.738)	(2090.884)	(1195.189)
RUEU(-2)*DUMMY	87.36606*	-250.785	56.94946	293.7895*	-69.4912
	(49.57368)	(167.696)	(115.9545)	(147.818)	(73.04957)
YHGEU(-2)*DUMMY	408.5052	-5277.78*	1000.732	7486.383**	5805.392***
	(586.5143)	(2635.415)	(1005.409)	(2858.844)	(596.9478)
TERM(-1)*DUMMY	17.1121**	14.44778*	9.136811	14.08006	33.27242***
	(6.770548)	(8.043938)	(6.239489)	(15.76704)	(5.234326)
BORROW(-1)*DUMMY	-3.0345	-46.41*	25.92331	15.65289	29.87202***
	(7.450292)	(26.34724)	(16.86057)	(18.7047)	(6.99894)
R^2	0.375145	0.420169	0.428138	0.391854	0.354808
Adjusted R^2	0.111318	0.175352	0.186686	0.135082	0.082394
Wald F-Statistic	289.2521	56.22876	23.23987	30.34687	251.6478
Prob (Wald F-statistic)	0	0	0	0	0

Note. We intend from running the country-level regressions to show that the global significance is preserved when the model is applied for each country individually and corrected for both heteroscedasticity and autocorrelation. This is reflected in a probability of Wald F-statistic that equals zero for all countries. Despite the significance of the model on a country level we rely on the pooled regression specification in our analysis because it boosts the power of our statistical analysis by allowing us to exploit both cross-sectional and time-series variations in country-level portfolio returns and country-level predictors. Moreover, pooling the observations in a panel data setting solves correlation and small sample problems of country-level regressions, which grants our inference more validity. The notation in this table is similar to that in table 3: *inc*, *ru* and *yhg* are the country level macroeconomic indicators employed from quarter *t-2* and representing income growth, relative unemployment rate and yearly growth in a house price index respectively. *inceu*, *rueu* and *yhgeu* are the same indicators on a Eurozone level, also utilized with a lag of two quarters. *div* is defined as log (1+dividend yield) of country portfolios employed from quarter *t-1*, *term* and *borrow* are the term spread and borrowing spread respectively also lagged by one quarter. *crisis* is a dummy variable that assumes a value of 1 in the financial crisis (2008Q1-2011Q3) and zero otherwise.